THREE ESSAYS IN JAPANESE HOUSING MARKET

BY

TAISUKE SADAYUKI

DISSERTATION

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Doctoral Committee:

Professor Geoffrey Hewings, Chair
Professor Daniel McMillen
Professor Anil Bera
Assistant Professor Bumsoo Lee

Abstract

In Chapter 1, the relationship between condominium price and the collective action problem associated with condominium reconstructions in Japan is discussed. Condominium reconstruction involves a difficult collective decision-making process among owners, which prevents older condominiums from being redeveloped efficiently. In Japan, more than one million condominium units remain unable to satisfy earthquake-resistance regulations, while only 211 condominiums had been rebuilt by April 2015. This paper provides empirical evidence (by examining the price differential, as controlling for rent, between condominiums and single-owner rental apartments) that a significant cost is associated with collective action problems surrounding condominium reconstructions in Japan. In particular, the condominium price declines by 3.7% as the number of owners in a complex doubles, while the number of owners does not affect the price of rental apartments. Also, the depreciation rate of condominium price is greater than the rate of the price of rental apartments. These findings are consistent with the prediction from the development model, that collective action problems surrounding the condominium reconstruction deteriorate the condominium price. A comparative examination of condominiums in Japan and the United States suggests that revising the current Japanese condominium law could induce more efficient development of old condominiums.

In Chapter 2, the externality of stigmatized properties and the interpretation of hedonic estimates are examined by using housing data in Tokyo, Japan. A stigmatized property is a real estate property that suffers from an undesirable past event, such as a suicide or homicide. The first part of this paper provides the empirical evidence of the existence of the negative externality of stigmatized property, based on data on rental housing and stigmatizing events recorded in Tokyo, Japan. The result shows that an incidence of homicide has a significant negative effect on the rent of a unit in the same apartment building: the rent decreases by about 20% in the following year of the incidence and recovers after 10 years. The second part of the paper discusses implications of hedonic estimates when prospective renters do not have complete information about stigmatized properties available in the data. Since hedonic coefficients do not represent implicit impacts of stigmatizing events in the presence of incomplete information, the implicit

impacts are investigated by imposing several assumptions; the results reveal that homicide are still likely to have a significant impact.

In Chapter 3, an empirical approach to estimate the special effect of multiple sites is proposed. Geographical relationships between a housing unit and the surrounding major sites, such as public transportation and crime scenes, are fundamental factors that determine the value of housing. In this paper, an empirical model is developed to estimate the spatial effect of such multiple sites that addresses the following three assumptions: (1) the closer a site, the greater the impact may be; (2) the impact differs by the characteristics of a site; and (3) the higher the ranking of proximity to a site, the greater the impact may be. In this model, a simple and interpretable proximity measure is constructed, representing the aggregate effect of surrounding sites. An empirical application is provided by using rental housing data in Tokyo, Japan, to examine how the clustering of train and subway stations influences the surrounding housing rental prices. The results suggest that at least the three nearest stations (and at most the five nearest stations) from each housing unit need to be considered in the hedonic model. The results also suggest that the nearest station has more influence on the rental price than do the second and third nearest stations, as mentioned in assumption (3). The proposed methodology can be applied to various spatial topics as transportations, foreclosures and polycentric cities.

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Chapter 1. The Collective Action Problem in Japanese Condominium Reconstruction

1.1. Introduction

Condominiums provide a mixture of private ownership of a defined apartment unit and co-ownership of a range of common property in the condominium complex, including hallways, roofs, elevators, gymnasiums, and swimming pools. The economies of scale and the public goods property of commonly owned facilities are two of the main reasons the number of condominiums has grown rapidly in Japan since the 1960s. By 2014, Japan had about six million condominium units, which accounted for about 10% of the total number of housing units in the country.

Although the co-ownership aspect of condominiums certainly provides property owners with various benefits, it frequently causes externalities and collective action problems. Substantial resources and effort are required to achieve collective decisions on condominium management, and still more resources and greater efforts are required for condominium reconstruction. In 2014, over 20% of condominiums (some 1.4 million units) were more than 30 years old and required extensive renovation. Many of these older condominiums were built before the revision of the Building Standards Act in 1981, so they do not satisfy earthquake-resistance regulations and carry substantial risk to society.[1] Nevertheless, only 211 condominiums had been rebuilt by April 2015. In the very near future, more owners of condominium units in urban Japan will face the difficult problem of reconciling conflicts of interest among themselves about reconstruction.

The main reason for the reconstruction problem in Japan seems to be the lack of effective condominium declarations that minimize the cost of the decision-making process. To reconstruct a condominium, Japanese condominium law requires at least four-fifths agreement among condominium owners.[2] Once the proposal for reconstruction is adopted, the approvers are supposed to buy out dissenting owners' units at the prevailing prices. However, because the

[1]The Construction Ministry (2006), now the Ministry of Land, Infrastructure, Transport and Tourism, has estimated the average housing life span based on the age of housing units demolished. The estimated average life span of a housing unit in Japan is about 26 years, which is shorter than in many Western countries (44 years in the United States and 75 years in the United Kingdom).

[2]In principle, Japanese law does not allow an old condominium to be terminated and redeveloped for a different use; it allows only the reconstruction of a new condominium, which is different from the laws in most western countries.

prevailing prices are ambiguous, owing to the absence of actual property transactions on the market, dissenters can set an arbitrarily high price for their units and impede the progress of the reconstruction. This is typical of the holdout problem itself.[3] Before 2003, most of the reconstruction projects in Japan occurred only when there was unanimity among owners (West and Morris, 2003, p. 918).

Aside from the Japanese condominium law, the tenure security law in Japan exacerbates the collective action problem. When reconstructing condominiums, owners consenting to reconstruction not only have to persuade dissenting owners to comply, but also have to evict any renters. Since the tenancy law excessively secures renters against eviction, it reinforces condominium law in discouraging the incentive for rebuilding.

The aim of this paper is to examine whether the decision-making process surrounding collective action carries a significant cost in Japanese condominium reconstruction. The empirical results we find when using data on rental units and owner-occupied units in condominiums along with data on rental apartments in Japan are consistent with the implication that condominium reconstruction involves a significant cost associated with collective action problems and that a revision of the current Japanese law may promote an efficient use of the land on which old condominiums are situated.

This paper is structured as follows. Section 2 discusses the rationale for using the number of units in a condominium as a proxy for the difficulty of collective decision-making based on previous literature as well as on an empirical examination of the relationship between the number of owners and the collective action time in reconstruction.[4] However, the number of units influences the price not only through the collective action problem, but also through other factors related to housing characteristics. Hence, Section 3 explains a simple development theory[5] and the empirical strategy used to identify the cost of collective action. In short, in the price function, we use the number of units along with the rent to control for the quality of housing. The price functions between condominiums and rental apartments are compared because the latter are

[3]Grossman and Hart (1980) argue that holdout problems make it impossible for developers to make a takeover bid. See also Menezes and Pitchford (2004), O'Flaherty (1994), and Plassman and Tideman (2010) for the relationship between land assembly and the holdout problem.
[4]Only the main findings of the empirical examination of the number of units and the negotiation time for reconstruction are described in Section 2. Details of the estimation results are demonstrated in Appendix A.
[5]Details of the development model are described in Appendix B.

owned by single owners and do not involve the collective action problems related to reconstruction. The data and estimation results are then described in Section 4. In Section 5, we use the National American Housing Survey (hereafter referred to as AHS), conducted by the U.S. Census Bureau, to compare Japanese condominiums with U.S. condominiums, where distinctly different condominium laws are enforced. In Section 6, the robustness of the findings is checked. Section 7 provides concluding remarks.

1.2. Number of Units in a Condominium and Collective Action

The difficulty of collective action involved in reconstruction is critically dependent on the extent to which interests differ among condominium owners. If the interests of condominium owners are alike, there is little room for conflicts of interest and divergent opinions regarding reconstruction. No transaction costs will then arise from the decision-making process. However, unit owners' interests can differ in many respects, based on the owners' ages, incomes, expectations about future rental prices, the extent of any liquidity constraints, and the opportunity costs involved in collective action.

As noted earlier, Japanese condominium law requires a high degree of uniformity among owners to initiate a reconstruction. As one can imagine, the collective decision-making process involved in condominium reconstruction becomes more complicated and inefficient as the number of owners increases. Strange (1995) models a bargaining game of land assembly in which landowners separately accept or respond with counteroffers based on the developers' bids. He shows that equilibrium prices and the likelihood of failing to complete the agreement rise with the number of landowners. Eckart (1985) also draws the same conclusion under a similar setting of a land assembly bargaining game. He finds that the aggregate counteroffer for land becomes lower when collusion exists among landowners compared with when they make decisions separately.

Olsen (1965) provides a seminal study on the relationship between group size and collective action. Regarding condominiums, Hansmann (1991) and Barzel and Sass (1990) discuss the difficulty of collective decisions among large numbers of owners from a legal and economic point of view. West and Morris (2003) report on collective decision making in condominium reconstruction projects after the Kobe earthquake in 1995. They find a negative relationship between the number of units in a condominium and the speed of collective decision making in reconstruction.

In Appendix A, data on completed condominium reconstruction projects in Japan are used to examine the collective decision-making time owners spend reaching a consensus on reconstruction. The results reveal that the increase in the number of units in a condominium significantly prolongs the collective decision-making time; when the number of units doubles, the time needed for collective decision-making is extended by about 30%. If condominium owners are aware of the future reconstruction problem in advance, they may begin collective action at an earlier stage, to carry out the reconstruction at the optimal timing. However, further results in Appendix A show that the number of units does not influence the starting time of the negotiation process. These results imply that an increase in the number of condominium owners not only prolongs the negotiation on reconstruction but also delays the reconstruction from occurring at the optimal timing. Based on previous studies and the present empirical results, it is assumed that the number of unit owners of a condominium can be used as a proxy variable for the collective action cost in the following analysis.

1.3. Estimation Strategy

Summary

The property value is determined by the net present value of expected future rental prices that represent the expected value of housing quality and the housing environment throughout the future. It can be shown, using a simple development model, that a delay in future reconstruction from the optimal timing and an increase in the collective decision-making cost degrade the condominium price and accelerate the decrease in that price. If it is assumed that discounting factors, including the property tax rate and depreciation rate, are expected to be constant in the future, the property value can be considered a function of the current rent, the depreciation rate, the expected future rent of a later reconstructed condominium, and the opportunity cost associated with the collective action problem. The development model predicts that the number of units, as a proxy for the collective action cost, negatively affects the condominium price with respect to the collective action problem with reconstruction. A detailed description of the model can be found in Appendix B.

However, in the empirical setting, one cannot examine the collective action cost simply by looking at the coefficient of the number of units in a standard hedonic price function because the number of units is possibly correlated with the rent, reflecting housing quality and services, through which the price may be "indirectly" affected. The number of units may be correlated with various amenities of the condominiums, such as the presence of a luxurious lobby, pool, and high-quality security system. In this regard, it is important to have information not only on the price of a condominium unit, but also the rent for a specific unit. Therefore, the building fixed-effect rent function is estimated first using data on condominium units for rent, from which fitted rent prices for all units in the same condominiums can be computed. Data are available on units for sale in the same condominiums where data on units for rent are obtained.

Recall that, as described in Appendix B, if it is assumed that the expectations for the future discounting factors stay constant, the current price can be expressed as a function of the current rent, the depreciation rate, and other price-specific factors, such as the property tax rate, interest rate, and collective action problem in the future reconstruction. Using data on the number of condominium units for sale, we estimate the price function as a function of the fitted rent along with the number of units and the age of the building. The discounting factors, such as the property tax rate and interest rate, can be omitted by introducing purchase-year dummies in the price function. The coefficient of the number of units in this price function is a price-specific effect that is not about the amenities or locational characteristics of the condominium, which are fully reflected in the rent.

Although the effect of the number of units on the price reflects mostly the collective action cost after controlling for rent, the price function of condominiums are compared with those of rental apartments to examine the robustness of the implication because rental apartments are owned by single owners and do not naturally involve collective action problems associated with reconstruction. If the collective action cost of the reconstruction problem is not negligible, a statistically significant negative impact should be expected on the number of units on the condominium price but not on the price of rental apartments.

The development model also predicts that the collective action problem associated with condominium reconstruction accelerates the depreciation of the property price. In this regard, the coefficients of the age of the building in the price functions can be compared between condominiums and rental apartments. The expectation would be that the depreciation rate of the price is greater for condominiums than for rental apartments. A similar comparison can be made between the coefficients of a cross-term for the number of units and the age of the building between condominiums and rental apartments to test the hypothesis implied by the model, where a negative sign for condominiums would be expected but not for rental apartments. To describe the estimation strategy more clearly, below the rent function to be estimated is explained, followed by the price function, and finally, the comparison of property values between condominiums and rental apartments.

Rent Function

The following equation is the log-linear rent function of condominiums:

$$\ln(RENT_i) = \beta_b + \boldsymbol{\beta}_1\mathbf{x}_i + \varepsilon_i^R, \tag{1.1}$$

where subscript i indicates a condominium unit and b is a condominium building to which i belongs. β_b is an unobservable fixed effect of condominium b on the rent, $\mathbf{x}_i$ is a column vector of unit-specific housing characteristics, $\boldsymbol{\beta}_1$ is a raw vector of parameters corresponding to $\mathbf{x}_i$, and ε_i^R is an error term. The variables in $\mathbf{x}_i$ include the floor number of the unit, the number of bedrooms, and dummy variables indicating whether the unit has south-facing window(s) and whether the unit is located at the corner of the floor.

It is important to reemphasize that the collective action problem associated with reconstruction has nothing to do with the rent because collective action matters to condominium owners but not to tenants, whereas the current rent reflects only the current quality of housing. However, the number of units may have externalities for residents because of the public goods property in the condominium, affecting the rent by which the price alters. For instance, if a larger condominium complex has more luxurious amenities, the number of units is positively correlated with the rent; thus, it has a positive effect on price through the rent. In the same way, in whatever way the number of units is correlated with the rent, it can indirectly influence the price in addition to the collective action problem associated with reconstruction. Therefore, the building fixed-effect rental price function of condominiums is estimated by using samples of condominium units for rent. Thereafter, fitted rent in the price function is provided, using samples of units for sale in the same condominium buildings, to control for the housing quality and services to extract the price-specific effects.

Price Function

The property value is determined by the net present value of expected future rental prices. Assuming constant discounting factors, the condominium price can then be expressed as a function of the current rent, the depreciation rate, the expected rent from a later reconstructed condominium, and the cost related to reconstruction. As suggested previously in the literature and through the empirical examination in Appendix A, the number of units not only delays the reconstruction, but also increases the reconstruction-related costs, such as the difficulty in the collective decision-making process and a holdout problem among the owners. Therefore, in terms of the collective action problem, the number of units should have a negative influence on the condominium price. To examine this hypothesis, the following price function for condominiums is estimated:

$$\ln(PRICE_i) = \gamma_j + \boldsymbol{\gamma}_1\mathbf{z}_i + \gamma_2 \ln(RENTHAT_i) + \gamma_3 \ln(UNITS_i)$$

$$+\gamma_4 \ln(AGE_i + 1) + \varepsilon_i^P , \tag{1.2}$$

where the subscript j is the region to which unit i belongs, ln(*RENTHAT*) is a fitted rent estimated in equation (1.1), *UNITS* is the number of units, and *AGE* is the age of the building. The vector $\mathbf{z}_i$ is a column vector of other variables that may directly affect the condominium price rather than affecting the price through rent, and ε_i^R is an error term. By introducing year dummies, discount variables, such as the interest rate and the property tax rate, are omitted because they are constant across the study area at any given year. In addition, γ_j controls for unobserved municipality-level regional fixed effects. The coefficient of the number of units, γ_3, reflects the price-specific effect of the number of owners, which is expected to show a negative value if the effect of the collective action problem on reconstruction is severe.

The cross-terms of unit number and building age are used as explanatory variables to capture the effects indicated in the development model, yielding following alternative equation:

$$\ln(PRICE_i) = \theta_j + \boldsymbol{\theta}_1\mathbf{z}_i + \theta_2 \ln(RENTHAT_i) + \theta_3 \ln(UNITS_i)$$

$$+\theta_4 \ln(AGE_i + 1) + \theta_5 \ln(UNITS_i) * \ln(AGE_i + 1) + e_i^P . \tag{1.3}$$

Here, the hypothesis is that $\theta_5 < 0$ under the influence of the collective action cost; that is, the more severe the collective action problem in reconstruction, the higher the rate of depreciation in the property price.

Condominiums Versus Rental Apartments

The coefficient for the number of units in the price function shows mostly the cost associated with the delay in reconstruction and the difficulty of collective decision making in condominiums for the following two reasons. First, the building fixed-effect rent function is estimated so that all unobserved effects of the number of units on the rent are captured by the predicted rent in the price function. Further, to our knowledge, the collective action problem is the only channel through which the number of units can directly affect the condominium price (i.e., not through the rent). Therefore, it can be expected that γ_3 will have a negative value if the collective action cost of the reconstruction problem is significant for condominiums.

In this research, however, the possibility of unrevealed factors other than the collective action problem is acknowledged, according to which the number of units would affect the price. The issue is treated by comparing the estimates of the price functions between condominiums and rental apartments. The building structures of rental apartments are indistinguishable from those of condominiums. However, unlike condominiums, rental apartments are owned by single owners or securitized into a real estate investment trust (REIT) by single corporations; thus, they do not require collective action. Accordingly, one might expect that the number of units would have a negative impact on the condominium price because of the collective action cost, whereas it will have no impact on the price of a unit for rental apartments.[6] In addition, the development theory in Appendix A implies that the speed of decline in the Japanese condominium price will be faster than that for a rental apartment that does not have the collective action problem of reconstruction.

Note that for rental apartments, the actual rent, *RENT*, is used in the price function instead of the predicted rent because, unlike condominiums, both a rental revenue and a price on each of the samples for rental apartments are observed. The next section explains the data on condominiums versus rental apartments.

1.4. Data and Estimation Results

Data

[6]Schill et al. (2007) estimate the price functions of condominiums and cooperative housing, respectively, and report that owners of cooperatives have lower costs in the collective decision-making process than do owners of condominiums. They also find similar results, namely, that the number of units in the condominium has a negative coefficient, although they do not use "rent" data.

The data consist of two types of apartments, condominiums and rental apartments.

Condominiums: First, data on Japanese condominiums are obtained from Tokyo Kantei, an independent real estate information service.[7] The data include unit (parcel)-specific information, such as the offered rent (if the sample unit is for rent) or the offered price (if the sample unit is for sale), number of floors, floor space, number of bedrooms, and so forth, and building-specific information, such as the building age, number of stories, number of units, and time to the central business district. These condominium samples were collected in 2005 for the Tokyo area alongside Japan Railway's Chuo, Keio, and Odakyu lines.

The Japanese condominium data provided by Tokyo Kantei have two issues. First, the data do not reveal whether each rental unit belongs to a condominium or a rental apartment. Thus, samples can be used only in buildings that have both units for sale and units for rent to ensure that they are in condominiums. Secondly, data on the rent and on the prices of condominiums are not transaction data, but rather the monthly listed prices provided by condominium owners. To extract price and rent data that are comparable with transaction prices, when samples are listed consecutively for multiple months, only the most recent observations are used because samples in the sale or rent list disappear once transactions take place. Samples are excluded if the floor space, rent per floor space, or price per floor space is above the 99th percentile or below the first percentile among condominium samples. Finally, the sample size for rent is 679 units within 370 condominium buildings, and the sample size for sale is 577 units within 303 condominium buildings.

Rental apartments: Data on rental apartments include asset sales prices of the buildings and their annual rental revenues and attributes, the information derived partly from Tokyo Kantei and partly from Japan REIT (JREIT).[8] For the data provided by Tokyo Kantei, the most recent observation is used when the same sample building appears repeatedly for multiple months, as in the sample selections of condominiums. In contrast, the data by JREIT provides transaction values. The price and rent data provided from Tokyo Kantei are from 2005, whereas for JREIT, the rent data ranges from 2005 to the first half of 2006 and the price data ranges from 2002 to

[7]For Tokyo Kantei, see the company home page (http://www.kantei.ne.jp; in Japanese).
[8]For JREIT, see the home page (http://index.ares.or.jp/index-en.php).

2006.[9]

Unlike the condominium data, the price and rent data for rental apartments is for the building, not for the apartment unit. The price is the sale price of a building as the ownership changes or someone purchases a newly constructed building to run a rental apartment. These data come along with the rent for the same building, which is the annual rental revenue from the tenants. The data also show the vacancy rate and the number of operation dates for each year and various building characteristics, such as the number of units, the year of completion, the number of stories, the total floor area, the presence of elevators, and so forth. As before, samples are excluded if the floor space per unit, rent per floor space, or price per floor space is above the 99th percentile or below the first percentile among rental apartment samples. Finally, the sample size used in the rent function is 502 and the sample size used in the price function is 477 rental apartment buildings.

Accordingly, the data on condominiums and rental apartments differ. The data on condominiums are compiled by housing unit (rent or price per unit, floor space per unit, etc.), whereas the data on rental apartments are compiled by the whole building (annual rental revenue or price of the building, total renter-occupied floor area in the building, etc.). Accordingly, a floor-unit price is estimated (i.e., the price divided by the floor space) and monthly floor-unit rent (i.e., for a condominium unit, the monthly rental price divided by the floor space, and for a rental apartment, the monthly rental revenue divided by the occupied floor space) to allow the estimates to be comparable between the two apartment types.[10] Table 1.1 defines the variables used in the rent and price functions, and Table 1.2 provides descriptive statistics.

Estimation Results

Rent function: The result in the first column [3-1] of Table 1.3 is the rent function of Japanese condominiums based on equation (1.1); since it estimates building fixed effects, only the coefficients of unit-specific variables are reported. A higher floor level and fewer bedrooms are associated with higher rent per floor area. The negative correlation between the number of bedrooms and the rent per floor area is due to the economy of scale, where the average fixed

[9]Dummy variables for years of purchase are included in the price function to control for the impact of changes in interest rates and property taxes on prices induced by the macroeconomy.

[10]For rental apartments, the monthly rental price per square meter is computed as the monthly rental revenue divided by the floor area of occupied units, whereas the price per square meter is computed as the purchase price divided by the floor area of all units.

rental cost per floor area (such as the usage of the kitchen and bathroom) decreases as the number of bedrooms increases.

In addition to equation (1.1), the rent functions for both condominiums and rental apartments are estimated by using municipality-level regional fixed effects (instead of building fixed effects) such that the effects of building-specific variables (such as the number of units, the age of the building, and the time to the central business district) between the two types of apartments can be compared. The second and the third columns, [3-2] and [3-3], show the rent functions of condominiums and rental apartments in Japan, respectively. The number of units has a negative effect on the rent for Japanese condominiums but has no effect for rental apartments. Moreover, the depreciation rate for rental apartments is lower than that for condominiums. One possible reason for these results is a lack of efficient major building maintenance that requires consensus with more than three-fourths agreement among property owners. A moral hazard among owners regarding common-area maintenance may become more severe in a condominium with a larger number of owners, potentially resulting in lower rent and a higher depreciation rate. On the other hand, an owner of a rental apartment can maintain the common area to maximize the property value without a collective action problem.[11]

Price function: The price functions for condominiums is estimated using the fitted rent from equation (1.1). The estimation results of price functions based on equations (1.2) and (1.3) are shown in columns [4-1] and [4-2] in table 1.4, respectively. On the other hand, for rental apartments, the actual rent data are used in the price function. The results are shown in columns [4-3] and [4-4].

According to the results in column [4-1], the condominium price decreases by 3.73% when the number of units doubles. In contrast, the number of units has no significant effect on the price of rental apartments in column [4-3]. As stated before, the difference in coefficients of the number of units on the price between condominiums and rental apartments is likely to be attributed to the magnitude of the collective action cost of the reconstruction problem. This result is consistent with the implication that the collective action cost of condominium

[11]Condominium owners are reluctant to engage in building maintenance because of problems with free riders. One way to keep a condominium building maintained frequently is to outsource the management to a third party under the provisions of condominium management. Chu et al. (2013) analyze a survey of condominium owners in Taipei and show that efficiency in the provision of condominium management improves with the level of effort owners expend on management committees.

reconstruction is significant in Japan. Furthermore, the coefficients of ln(AGE + 1) in columns [4-1] and [4-3] indicate that the price depreciation rate for condominiums is much higher than the rate for rental apartments, as predicted in the model.

Last, according to the results in columns [4-2] and [4-4], the coefficient of the cross-term, ln($UNITS$)*ln(AGE + 1), is negative and significant for Japanese condominiums, whereas it is not statistically significant for rental apartments. This finding is also consistent with the implication from the development model that the deterioration rate accelerates as the collective action problem becomes more severe.[12]

1.5. Additional Analysis: U.S. Condominiums

In this section, the results are provided for similar analysis discussed in the previous section, using U.S. data from the American Housing Survey (AHS). The purpose of this section is to compare the collective action cost between two countries with distinctly different legal systems. An empirical comparison across countries usually requires elaborate data across multiple markets. Nevertheless, utilization of the imputed rent in the price function helps separate the price-specific effect from the "indirect" effect through rent such that our comparative analysis of the collective action problem becomes highly plausible, even with limited variation in the data samples. Although a future examination with extended data sets would be helpful to gain further insight into the collective action problem, some valuable insights can be obtained from the provisional results of this comparative analysis between the United States and Japan. As shown in the following discussion, these results suggest that the owners would potentially benefit from a revision in the Japanese laws surrounding condominium redevelopment. Some brief discussion is provided to suggest why many state laws governing condominiums are more efficient than the Japanese law in terms of condominium redevelopment, and then show empirically that the number of units does not decrease the condominium price in the United States.

[12]One of the dissertation committees expresses his concern of a possibility that the expectations on the future rents may be different across regions and thus, influence the price. In the price function, we control for the unobserved regional effects on the price by using municipality-level fixed effects for condominiums. However, more detail data is required to control for the expectations specific to smaller regional levels. Consequently, we estimate an alternative price function with an additional independent variable about the distance to CBD because the future rent may be expected to be higher near CBD. The implication of the result remains the same.

Condominium Law

As described earlier, Japanese condominium law defines very specific provisions for enforcing the procedure for condominium reconstruction, which creates the potential risk of inducing a holdout problem. As a result, most of the reconstructions in Japan occur only when unanimity is reached among owners. In contrast, most of the state laws in the United States have no defined rules regarding the decision-making process involved in condominium reconstruction. Instead, a condominium can be terminated by voting, which usually requires four-fifths or three-fourths agreement, depending on the state laws and bylaws. After a resolution is passed to terminate the condominium, the general procedure is to sell the land to a new developer and redistribute the revenue to previous condominium owners according to their individual ownership.[13]

In principle, this termination rule has two advantages over Japanese condominium law. First, because the amount of redistribution is unambiguous, it leaves no room for a holdout among dissenters once the resolution is passed, and proponents do not need to expend time and effort persuading dissenters to leave the condominium. Secondly, as long as no other regulation governing the land exists in that particular area, it can be developed in any manner after the condominium is terminated, thus maximizing the value of the land.

In contrast, Japanese condominium law allows only condominiums to be rebuilt as a means of redevelopment. Moreover, before December 2014, selling a condominium and the land to a third party was not allowed unless unanimous agreement was achieved. Since December 2014, a revision to the law reduced the requirement for agreement to four-fifths. However, several conditions must still be met to sell a condominium and the land; for instance, the land cannot be developed for any other use than building a new condominium, and this law applies only to condominiums that do not meet the earthquake-resistance standard.

In addition, many states in the United States allow condominium developers to stipulate rules through private contracts, including covenants, conditions, and restrictions (CC&Rs).[14] These rules can contribute to maintaining the quality of services in the common facilities and may avoid the risk of decreasing the price of the condominium by allowing developers to stipulate the

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[13]The National Conference of State Legislatures has a website listing state laws related to condominiums (http://www.ncsl.org/research/environment-and-natural-resources/state-condo-laws.aspx).
[14]See West and Morris (2003, p. 925).

optimal declaration rules regarding collective decision-making. Barzel and Sass (1990) argue that declarations and bylaws may help internalize the externalities caused by the behavior of property owners, thereby minimizing the cost of collective action. In brief, the collective action cost for condominium management in the United States seems to be remarkably lower than in Japan.

Empirical Strategy and Data

The same estimation procedure as for Japanese condominiums is employed: the rent function is estimated from data on condominium units occupied by tenants, and this imputed rent is used to estimate the price . The data are obtained from the AHS[15] for 2002, 2004, 2005, and 2007. Sample are taken from housing types in the "condominium or cooperative" category. Those above the 99th percentile or below the first percentile for floor space, rent per floor space, or price per floor space among the AHS samples are excluded. The sample sizes are 562 for rental units with rental prices and 1058 for owner-occupied units with prices.

Two distinctions can be found in the data between Japanese and U.S. condominiums. First, unlike the data on Japanese condominiums, each sample in the AHS belongs to a different building. Therefore, metropolitan statistical area fixed effects are used (instead of building fixed effects) along with building-specific variables (e.g., number of units, age of the building, time to work places, etc.) and unit-specific variables (i.e., number of units and floor level) when estimating the rent function. Secondly, a sample in the AHS shows the transaction price if the household owns the property, or it shows the current rental payment if the household rents the property. Accordingly, in the price function, purchase-year dummies are included, over the period from 1963 to 2007, as well as data-year dummies (2002, 2004, 2005, and 2007) and regional fixed effects (metropolitan statistical area, SMSA). Regarding the other explanatory variables, we use the same variables as for Japanese condominiums except for *SOUTH*, *CORNER*, and *RENOVATED* that are not available in the AHS.[16]

Estimation Results

Rent function: The estimation results for the rent function are shown in the first column [5-1] of

[15]Microdata on the AHS were obtained from the United States Census Bureau website, available at http://www.census.gov/housing/ahs/.
[16]Tables 1.3 and 1.4 present definitions of and basic statistics for the variables, respectively.

table 1.5. In contrast to Japanese condominiums, the number of units is positively correlated with the rent for U.S. condominiums. There are many possible reasons for this. To name a few, a condominium with a larger number of units may have more ample amenities (e.g., exercise facilities) than a small condominium, which outweighs the negative externality of the number of units on the rent. In addition, with SMSA-regional fixed effects in the regression, the positive coefficient for the number of units may imply an endogenous sample bias among condominiums within an SMSA. Taking into account that the number of stories is positively correlated with the rent, a neighborhood with a higher population density in the United States (i.e., the area where condominiums have greater numbers of units) may be tend to be richer than a neighborhood of condominiums with a lower population density.

From this international comparative analysis, we can barely obtain a valid interpretation of the differences in rent functions because such a comparison involves addressing many unobservable factors. However, there is a sizable advantage of using the predicted rent in the price function because it enables separation of the price-specific effect of the number of units from whatever the indirect effect on the price through rent might be.

Price function: The results in columns [5-2] and [5-3] show the price functions of condominiums in the United States based on equations (1.2) and (1.3), respectively. In the United States, the number of units does not significantly affect the condominium price directly, in contrast to the observed negative and significant effect for Japanese condominiums revealed in the previous section. In addition, the coefficient of the cross-term is not significant, although it shows the expected negative sign. These results are consistent with the interpretation that an increase in the number of owners of a condominium does not significantly impede the collective action, whereas the inefficiency in Japanese condominium law causes a serious collective action problem in Japanese condominiums. Considering that laws and land-use policies vary among states and cities in the United States, the data and empirical strategy need to be elaborated for further comparative analysis.

1.6. Robustness Check

This section provides a robustness check by examining the differences in coefficients for the rent and price functions among three types of apartments: Japanese condominiums, Japanese rental apartments, and U.S. condominiums. This is an attempt to deal with a problem that may arise from distributional differences in the housing characteristics among the three types of apartments. Log-linear functions are estimated that allow comparison of the estimation results among the different apartment types. If the elasticity depends on the level of a variable, distributions of the variable among different types of apartments do matter when its coefficients are compared. Ideally, one would like to evaluate the marginal effects of a variable at the same sample means among all apartment types. Specifically, the main interest is in the effects of the number of units and the age of the building on the price functions, whereas the basic statistics presented in table 1.2 show that samples of Japanese condominiums tend to be larger than samples of the other two types and tend to be older than samples of rental apartments in Japan.

With these factors in mind, a second analysis is conducted as follows. First, samples are selected by limiting the number of units and the building age. In particular, apartments are excluded that contain more than 105 units (the 95th percentile in the samples of rental apartments) and those built before 1981 (the year when the Japanese government introduced the new earthquake-resistance regulations). Secondly, a propensity score-matching method is applied to select rental apartments and condominiums in the United States whose characteristics, in terms of the number of units and the building age, are similar to those of Japanese condominiums.[17] The sample selections in the matching method are done by computing the propensity scores. These scores are estimated by the probit model using a dummy variable indicating the Japanese condominium as a dependent variable and the number of units and year of completion as explanatory variables. Samples are selected of rental apartments or U.S. condominiums whose propensity scores fall within a certain radius (caliper) of any scores computed for Japanese condominiums.[18] Finally, by pooling the data on Japanese condominiums with data from another selected data set (either rental apartments or condominiums in the United States), the rent and price functions are estimated with cross-terms of variables and a dummy variable indicating Japanese condominiums. The coefficients of the cross-terms reveal the differences in the magnitudes of coefficients between Japanese condominiums and the other apartment

[17]See Deng et al. (2012) and McMillen (2012) for applications of propensity score-matching methods in the housing market, demonstrating how these can be used to construct a housing price index by matching housing samples having similar characteristics.

[18]We do not use other building characteristics in the matching procedure because our interest is in checking the robustness of the effects of two variables, the number of units and the building age, in the price function while maintaining as many observations as possible. Using other variables, such as *TIME* and *STORIES*, in the matching procedure reduces the sample size so significantly that we would not have sufficient observations to carry out the comparative analysis.

types.

Japanese Condominiums Versus Japanese Rental Apartments

Estimations comparing Japanese condominiums with rental apartments are examined first. Table 1.6 shows the estimation results for the price functions. The first three columns correspond to the results based on equation (1.2), and the latter three correspond to the results based on equation (1.3). Each column shows an estimation using samples selected by a different range of calipers in the propensity score matching. Restricting the range of calipers from 0.5 to 0.1, the sample size is reduced. *D* in this table indicates a condominium dummy; therefore, cross-terms, such as D*ln(*UNITS*), show the difference in coefficients for the variables in the rent function for Japanese condominiums compared with the coefficients for rental apartments.

The estimation results are consistent with the results of the preceding estimations using separate data. In the first three columns, the coefficients for D*ln(*UNITS*) show that the condominium price declines by 4.5 to 5.3% relative to the price change in rental apartments when the number of units in the building doubles. Further, a significant difference is observed in the coefficient for ln(*AGE* + 1) between the two apartment types. Although the price of rental apartments decreases by approximately 6 to 8% as the age of the building doubles, condominiums devalue by an extra 18 to 21%. In the latter three columns, although the coefficients of D*ln(*UNITS*)*ln(*AGE* + 1) are statistically weak because of multicollinearity (with two of them being statistically significant at the 15% level), they show the expected negative signs.

Japanese Condominiums Versus U.S. Condominiums

In the same manner, condominiums in the United States are selected that are similar to Japanese condominiums in the number of units and age of the building, and then the rent and price functions are examined. Table 1.7 shows the estimated price functions. The coefficients of ln(*UNITS*) are all positive, indicating that residents in the United States expect a higher future rent for a larger condominium. As discussed, in the United States, the land on which condominiums are constructed can be used in various ways after the condominiums are terminated. In general, a highly productive property, such as a commercial facility and office building, requires a sufficiently large tract of land; in other words, economies of scale do not work for the smaller tracts of land where condominiums with a small number of units are located. Accordingly, the number of units, which is positively correlated with the size of the land, may have a positive effect on the price of condominiums in the United States.

In the first three columns, the coefficients for D*ln($UNITS$) and D* ln(AGE + 1) are negative and statistically significant, indicating that Japanese condominiums devalue more than condominiums in the United States as the number of units and the age of the building increase. In the latter three columns, although the significance of the effect of D*ln($UNITS$)*ln(AGE + 1) is weak (with one of the coefficients being statistically significant at the 15% level), the coefficients show the expected negative signs. These results are consistent with the implication that by introducing into an amendment on Japanese condominium law the possibility of terminating condominiums, the future productivity of land use along with condominium redevelopment could be improved. In future research, a more careful examination is needed to evaluate the explicit benefits of implementing such a policy.

1.7. Conclusion

The reconstruction of condominiums is becoming a serious social problem in Japan. More than 1 million condominium units in Japan were built over 30 years ago, and many of them do not meet the current earthquake-resistance standards. However, reconstruction is complex and involves a difficult collective decision-making process, which prevents older condominiums from being redeveloped efficiently. The purpose of this paper is to examine whether a collective action cost exists for Japanese condominiums.

The number of units is used as a proxy for the difficulty of collective action. The positive relationship between the number of owners and the collective action cost is addressed in a number of literature studies, both empirical and theoretical. In addition, using data on completed condominiums in Japan, the results reveal that an increase in the number of units prolongs the duration of collective decision making and delays the timing of reconstruction.

The price function of condominiums by is estimated by using the imputed rent, as predicted from the rent function, to differentiate the direct effect of the number of units on the price from the indirect effect of the number of units via rent. Data are also used on rental apartments to observe whether a difference exists between the price functions of two type of apartments, those with and those without the collective action problem. Using data on condominiums in the United States, an attempt is made to explore the significance of different condominium laws in the two countries.

The results show that, among the three types of buildings, the number of units negatively affects only the price of Japanese condominiums, and the rate of depreciation in the condominium price in Japan is greater than the rate for the other two. The distribution biases of variables of interest among different apartment types are evaluated and a comparison made of their price functions with those of selected samples by applying the propensity-matching method. The negative coefficients for the number of units and the age of the building in the price functions for Japanese condominiums are significantly lower than those for the other two types of dwellings. These results imply that a substantial cost is inherent in collective action problems associated with condominium reconstruction in Japan. Addressing the problem surrounding condominium reconstruction in Japan will not only contribute to the efficient use of land, but also improve the government finance through the increase in property taxes. If the number of units had no effect in the price function, local governments in Tokyo would gain ¥300 billions extra (about three billion dollars with an exchange rate of $1=¥100) in additional property tax revenue.[19]

Most of the condominium laws in the United States specify that a condominium should be terminated prior to development, and these laws allow the land to be developed in any manner as long as it meets area-specific regulations, such as land-use policies and building codes. In contrast, Japanese condominium law considers reconstruction as the only method of condominium redevelopment. Under Japanese law, the collective decision-making process in reconstruction is a mechanism that induces a serious holdout problem among owners. A recent revision of the Japanese law allows a condominium to be sold to a developer, yet the law still requires the reconstruction of a new condominium as the only means of development. Further studies with extended data on the collective action problem and condominium property values will be helpful in examining the policy implications of the Japanese law.

[19] The 300 billions is calculated based on the estimation result and statistics on Tokyo; the average condominium price in March 2016 (46,860,000 yen) by Tokyo Kantei http://www.kantei.ne.jp/index.php, the number of condominium units in August 2011 (1,754,814 units) by Tokyo Metropolitan Government http://www.toshiseibi.metro.tokyo.jp/, property tax rates (1.4% of an assessed property value for a condominium unit larger than 120 m^2 and 0.7% for a unit smaller than 120 m^2), and an assessed value which is usually about 70% of the transaction value.

1.8. Tables

Table 1.1. Variables in the rent and price functions.

Variable	Definition
Rent function	
RENT	Monthly rent per floor area (¥/m^2 or \$/ft^2)
UNITS	Total number of dwelling units in the apartment building
AGE	Age of the apartment (years)
TIME	Time (minutes) from the apartment to the central business district (for Japanese condominiums and rental apartments) or to the workplace (for U.S. condominiums)
STORIES	Number of stories in the apartment building
FLEVEL	Floor number of the unit
BEDRM	Number of bedrooms in the unit
EV	Binary variable indicating an apartment building with an elevator or more
SOUTH	Binary variable indicating a unit with south-facing windows
CORNER	Binary variable indicating a unit located on a corner of the floor
BRAND	Binary variable indicating an apartment managed by one of the eight most highly valued real estate companies (Mitsui, Nomura, Daikyo, Sumitomo, Tokyu, Tokyotatemono, Mitsubishizisyo, Touwa)
Data Year	Year dummies for data sources and time the property was purchased
Building	Building dummies for Japanese condominiums
Municipality	Municipality dummies for Japanese rental apartments
SMSA	SMSA (metropolitan statistical area) dummies for the U.S. condominiums
Price function	
PRICE	Price per floor area (¥10,000/m^2 or \$/ft^2)
RENTHAT	Fitted value of rent per floor area for Japanese and U.S. condominiums (¥/m^2 or \$/ft^2) or actual rent per floor area for Japanese rental apartments (¥/m^2)
UNITS	Total number of dwelling units in the building
AGE	Age of the building (years) at the time of purchase
RENOVATED	Binary variable indicating a unit maintained before selling
Data Year	Year dummies for data sources
Purchase Year	Year dummies for time the property was purchased
Municipality	Municipality dummies for Japanese rental apartments
SMSA	SMSA (metropolitan statistical area) dummies for U.S. condominiums

Table 1.2. Basic statistics on variables used in the rent and price functions.

Variable	Item	Unit	Minimum	Median	Maximum	Mean
RENT	[CJ]	(¥10,000/m^2)	0.12	0.29	0.55	0.30
	[RJ]	(¥10,000/m^2)	0.16	0.39	0.70	0.40
	[CU]	(\$/ft^2)	0.14	0.88	3.73	0.97
PRICE	[CJ]	(¥10,000/m^2)	13.92	44.71	94.29	44.86
	[RJ]	(¥10,000/m^2)	23.22	73.53	163.52	75.74
	[CU]	(\$/ft^2)	12.33	98.30	461.77	119.68
UNITS	[CJ]		6.00	94.00	1192.00	180.93
	[RJ]		3.00	29.00	288.00	39.73
	[CU]		2.00	10.00	747.00	37.99
AGE	[CJ]	(years)	0.00	22.00	46.00	21.70
	[RJ]	(years)	0.00	3.00	43.00	7.27
	[CU]	(years)	0.00	22.50	44.50	22.59
Year of completion	[CJ]		1959.00	1983.00	2005.00	1983.30
	[RJ]		1962.00	2003.00	2006.00	1998.44
	[CU]		1962.50	1982.50	2006.00	1981.52
TIME	[CJ]	(minutes)	0.00	2.00	3.00	1.54
	[RJ]	(minutes)	—	—	—	—
	[CU]	(minutes)	0.00	2.00	4.00	1.96
BEDRM	[CJ]		1.00	21.00	56.00	21.74
	[RJ]		3.00	15.00	55.00	17.54
	[CU]		0.00	20.00	180.00	22.58
FLEVEL	[CJ]		1.00	4.00	31.00	4.89
	[RJ]		—	—	—	—
	[CU]		1.00	1.00	21.00	2.10
STORIES	[CJ]		3.00	9.00	31.00	8.99
	[RJ]		2.00	7.00	30.00	7.51
	[CU]		1.00	2.00	21.00	3.56
BRAND	[CJ]		—	—	—	—
	[RJ]		0.00	0.00	1.00	0.11
	[CU]		—	—	—	—
EV	[CJ]		0.00	1.00	1.00	0.83
	[RJ]		0.00	1.00	1.00	0.65
	[CU]		0.00	0.00	1.00	0.20
CORNER	[CJ]		0.00	0.00	1.00	0.25
	[RJ]		—	—	—	—
	[CU]		—	—	—	—
SOUTH	[CJ]		0.00	1.00	1.00	0.60
	[RJ]		—	—	—	—
	[CU]		—	—	—	—
RENOVATED	[CJ]		0.00	0.00	1.00	0.09
	[RJ]		—	—	—	—
	[CU]			—	—	—

Notes: [CJ]: Condominiums in Japan; [RJ]: rental apartments in Japan; [CU]: condominiums in the United States.

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Table 1.3. Rent function.

	[3-1]	[3-2]	[3-3]
	Japanese condominium	Japanese condominium	Rental apartment
Building-specific variable			
ln(*UNITS*)		−0.0417***	0.0088
		(0.0088)	(0.0210)
ln(*AGE* + 1)		−0.1107***	−0.0307**
		(0.0126)	(0.0122)
ln(*TIME*)		−0.0744***	−0.0913***
		(0.0236)	(0.0346)
ln(*STORIES*)		0.0154	0.0546
		(0.0203)	(0.0440)
EV		0.0330	−0.0794*
		(0.0230)	(0.0422)
BRAND			0.0805***
			(0.0287)
Unit-specific variable			
ln(*BEDRM* + 1)	−0.1307***	−0.2790***	
	(0.0370)	(0.0125)	
ln(*FLEVEL* + 1)	0.0340***	0.0331***	
	(0.0131)	(0.0102)	
SOUTH	−0.0125	−0.0180†	
	(0.0187)	(0.0122)	
COURNER	−0.0122	−0.0083	
	(0.0210)	(0.0143)	
Fixed effect	Building (370)	Municipality (22)	Municipality (35)
Other dummy variables			Data year (2005, 2006)
Observations	679	679	487
R^2	0.9697	0.8241	0.5590

Notes: The dependent variable is ln(*RENT*). The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Values in parentheses below the coefficients are robust standard errors. Values in parentheses in the row of fixed-effect level are numbers of regional fixed effects in estimations. Coefficients of dummy variables for regions and years of data are not shown in the table.

Table 1.4. Price functions: Japanese condominiums and rental apartments.

	[4-1]	[4-2]	[4-3]	[4-4]
	Japanese condominium		Rental apartment	
ln(*RENTHAT*)	0.4659***	0.4597***	0.6885***	0.6863***
	(0.1273)	(0.1251)	(0.1069)	(0.1068)
ln(*UNITS*)	−0.0373***	0.0959†	0.0052	0.0206
	(0.0101)	(0.0604)	(0.0127)	(0.0195)
ln(*AGE* + 1)	−0.3273***	−0.1171	−0.0628***	−0.0302
	(0.0193)	(0.0889)	(0.0107)	(0.0305)
ln(*UNITS*)*ln(*AGE* + 1)		−0.0432**		−0.0108
		(0.0189)		(0.0102)
ln(*RENTHAT*)	Fitted value from [3-1]		ln(*RENT*)	
Fixed effect level	Municipality (21)		Municipality (35)	
Other dummy variables	*RENOVATED*		Purchase year (2002–2006)	
Observations	577	577	463	463
R^2	0.7934	0.7962	0.8444	0.8450

Notes: The dependent variable is ln(*PRICE*). The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Values in parentheses below coefficients are robust standard errors. Values in parentheses in the row of fixed-effect level are numbers of regional fixed effects in estimations. Coefficients of dummy variables for regions and years of data or purchase are not shown in the table.

Table 1.5. U.S. condominiums.

	[5-1]	[5-2]	[5-3]
	Rent function	Price function	
ln(*RENTHAT*)		0.4738*	0.4654*
		(0.2631)	(0.2603)
Building-specific variable			
ln(*UNITS*)	0.0489*	0.0300	0.0780**
	(0.0273)	(0.0311)	(0.0382)
ln(*AGE* + 1)	−0.1144***	−0.0897**	−0.0379
	(0.0338)	(0.0363)	(0.0566)
ln(*UNITS*)*ln(*AGE* + 1)			−0.0199
			(0.0163)
ln(*TIME*)	0.0375		
	(0.0276)		
ln(*STORIES*)	0.1181*		
	(0.0711)		
EV	0.0340		
	(0.0925)		
Unit-specific variable			
ln(*BEDRM* + 1)	−0.2247**		
	(0.0988)		
ln(*FLEVEL* + 1)	−0.0496		
	(0.0540)		
Dependent variable	ln(*RENT*)	ln(*PRICE*)	
ln(*RENTHAT*)		Fitted value from [5-1]	
Fixed effect	SMSA (73)	SMSA (85)	
Other dummy variables	Data year (2002, 2004, 2005, 2007)	Purchase year (1963–2007), Data year (2002, 2004, 2005, 2007)	
Observations	562	1058	1058
R^2	0.3263	0.4069	0.4079

Notes: The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Values in parentheses below coefficients are robust standard errors. Values in parentheses in the row of fixed-effect level are numbers of regional fixed effects in estimations. Coefficients of dummy variables for regions and years of data or purchase are not shown in the table.

Table 1.6. Price function: Condominiums and rental apartments in Japan.

	[6-1]	[6-2]	[6-3]	[6-4]	[6-5]	[6-6]
Caliper:	0.5	0.3	0.1	0.5	0.3	0.1
Rental apartments						
ln(*RENTHAT*)	0.6588***	0.6518***	0.7194***	0.6569***	0.6517***	0.7173***
	(0.1111)	(0.1098)	(0.1354)	(0.1096)	(0.1101)	(0.1342)
ln(*UNITS*)	0.0087	−0.0174	0.0134	0.0393*	−0.0140	0.0057
	(0.0149)	(0.0171)	(0.0213)	(0.0225)	(0.0350)	(0.0405)
ln(*AGE* + 1)	−0.0571***	−0.0801***	−0.0687***	0.0074	−0.0740	−0.0831
	(0.0108)	(0.0150)	(0.0188)	(0.0340)	(0.0581)	(0.0647)
ln(*UNITS*)				−0.0213*	−0.0018	0.0038
*ln(*AGE* + 1)				(0.0114)	(0.0162)	(0.0177)
Condominiums − rental apartments						
*D**ln(*RENTHAT*)	−0.4568**	−0.4497**	−0.5289***	−0.4565**	−0.4513**	−0.5297***
	(0.1806)	(0.1802)	(0.1989)	(0.1802)	(0.1810)	(0.1985)
*D**ln(*UNITS*)	−0.0800***	−0.0539*	−0.0834**	0.1595	0.2128	0.1933
	(0.0297)	(0.0309)	(0.0337)	(0.1648)	(0.1676)	(0.1708)
*D**ln(*AGE* + 1)	−0.2067***	−0.1837***	−0.1934***	0.0973	0.1787	0.1879
	(0.0385)	(0.0400)	(0.0420)	(0.2399)	(0.2454)	(0.2499)
*D**ln(*UNITS*)				−0.0761	−0.0957†	−0.1009†
*ln(*AGE* + 1)				(0.0600)	(0.0613)	(0.0625)
Observations	564	527	431	562	525	429
R^2	0.8683	0.8729	0.8865	0.8700	0.8736	0.8873

Notes: The dependent variable is ln(*PRICE*). The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Values in parentheses are robust standard errors. Coefficients of the constant term and dummy variables for condominiums, regions, and years of data or purchase are not shown in the table.

Table 1.7. Price function: Condominiums in Japan and the United States.

	[7-1]	[7-2]	[7-3]	[7-4]	[7-5]	[7-6]
Caliper:	0.5	0.3	0.1	0.5	0.3	0.1
Rental apartments						
ln(*RENTHAT*)	0.2175	0.5382	0.8418**	0.2242	0.6386	0.9335**
	(0.3845)	(0.4546)	(0.3552)	(0.3984)	(0.4563)	(0.3831)
ln(*UNITS*)	0.0780**	0.0891**	0.1211*	0.0861*	0.1194**	0.1613**
	(0.0371)	(0.0382)	(0.0709)	(0.0445)	(0.0475)	(0.0778)
ln(*AGE* + 1)	−0.0998***	−0.0849**	−0.0664	−0.1148†	−0.0188	0.0620
	(0.0316)	(0.0407)	(0.0561)	(0.0709)	(0.0814)	(0.1170)
ln(*UNITS*)				−0.0050	−0.0213	−0.0299
*ln(*AGE* + 1)				(0.0194)	(0.0213)	(0.0249)
Condominiums − rental apartments						
*D**ln(*RENTHAT*)	−0.1435	−0.4756	−0.7654*	−0.1502	−0.5790	−0.8548**
	(0.4162)	(0.4807)	(0.3903)	(0.4283)	(0.4818)	(0.4149)
*D**ln(*UNITS*)	−0.1509***	−0.1595***	−0.1936**	0.1131	0.0814	0.0389
	(0.0460)	(0.0468)	(0.0762)	(0.1757)	(0.1780)	(0.1912)
*D**ln(*AGE* + 1)	−0.1576***	−0.1732***	−0.1897***	0.2285	0.1306	0.0541
	(0.0503)	(0.0566)	(0.0694)	(0.2550)	(0.2616)	(0.2778)
*D**ln(*UNITS*)				−0.0931†	−0.0765	−0.0685
*ln(*AGE* + 1)				(0.0639)	(0.0653)	(0.0674)
Observations	709	599	500	709	599	500
R^2	0.6537	0.6677	0.6945	0.6518	0.6661	0.6939

Notes: The dependent variable is ln(*PRICE*). The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Values in parentheses are robust standard errors. Coefficients of a constant term, dummy variables for condominiums, regions, and years of data or purchase are not shown in the table.

Chapter 2. The Externality of Stigmatized Property

2.1. Introduction

A stigmatized property, or a psychologically impacted property, is a real estate property that suffers from an undesirable past event, such as a death by fire, a suicide, a homicide, or any other tragedy that affects the present value of the property. Although the definition of a stigmatized property is controversial and state laws vary in the United States,[20] the various definitions share the concept that a reduction in the value of a stigmatized property is associated with a psychological impact, not a material deficit (Brown and Thurlow, 1996; Sanchez-Behar, 2008; Edmiston, 2010). The general rule regarding a housing supplier's disclosure of a stigmatized property in the United States is *caveat emptor*, that is, "Let the buyer beware." No cause of action arises against suppliers of stigmatized properties for failing to disclose the fact that a stigmatizing event took place on the property. In contrast, Japanese property transaction law "prohibits suppliers from misrepresenting or intentionally failing to disclose a fact when concluding a contract if the fact has a critical influence on the transactional partners' decision,"[21] which certainly includes a past incident on the property such as a suicide or murder.

However, it is important to note that, in practice, in both the United States and Japan, housing suppliers have no obligation to disclose stigmatized properties to their customers if the transactional property is not the one in which the stigmatizing event took place. Because prospective renters have only partial information about the existence of stigmatized properties, some individuals may buy or rent housing without being aware there are stigmatized properties in the neighborhood, or even in the same apartment building. When such information is asymmetrical, housing suppliers strategically assign offered prices that maximize their expected discounted future revenues, conditional on what prospective renters would learn about the surrounding stigmatized properties. Consequently, suppliers do not adjust their offered prices to as low a level as when people are fully informed. This means that under incomplete

[20] The types of stigmatizing events listed in the statutes are mostly homicide, suicide, HIV, and AIDS, followed by "any other felony." The website Real Estate Webmasters (http://www.realestatewebmasters.com/) provides the following description of a stigmatized property: "[W]hile the exact legal definition varies by state and country, typically it is construed to be where something has taken place on a property (such as the death of one of the occupants in a traumatic or notorious fashion) such that it has affected the value of the property."
[21] Article 47, item 1, of the Building Lots and Buildings Transaction Business Act.

information, a hedonic approach does not reveal the implicit externality that is present under complete information, in which prospective renters are fully informed of the existence of stigmatized properties.

The first aim of this paper is to examine the existence of the externality of stigmatized properties. Although numerous empirical studies have been conducted on the externality of hazardous waste sites and environmental contamination,[22] to our knowledge, this paper is the first to examine the externality of stigmatized property.[23] Estimation results based on rental housing data listed in the housing market and on stigmatized properties recorded in Tokyo, Japan, verify the presence of a negative externality: the value of rental housing near stigmatized properties is low and increases as the properties are located farther from the sites. Furthermore, the strength of the externality is ameliorated as time passes after the stigmatizing event.

The second objective of this study is to investigate hidden factors behind coefficients of the hedonic model under incomplete information. Using the estimation results, two main hidden factors are explored in the latter part of this paper: 1) the externality under complete information, and 2) the information on stigmatized properties provided to prospective renters. As mentioned, although the estimates with hedonic models indicate that a negative externality is present for stigmatized property, they do not represent the degree of the externality under complete information.

To examine the relationship between incomplete information and the hedonic model, Kask and Maani (1992) studied the consequences on the hedonic price when consumers possessed incomplete information and believed in a biased subjective probability of a future event. The authors discussed the direction of biases in the hedonic price, depending on the information and the subjective probability that consumers possessed. Pope (2008a, b), on the other hand,

[22] See Boyle and Kiel (2001) for a literature review. For recent studies, see McCluskey and Rausser (2003a, 2003b), Inlanfeldt and Taylor (2004), Messer et al. (2006), Deaton and Hoehn (2004), Kiel and Williams (2007), and Gamper-Rabindran and Timmins (2011). Most of these studies estimate hedonic housing price functions by using the distance to hazardous sites as an explanatory variable to evaluate the degree of effect of the externality. Simons and Saginor (2006) and Braden et al. (2011) conducted meta-analysis of previous studies to investigate factors involved in the externality.

[23] Various articles and papers have reported how much stigmatized properties are devalued relative to nonstigmatized properties. For example, Larsen and Coleman (2004), who conducted a survey of real estate licensees in Ohio, found that the sale prices of stigmatized properties were, on average, approximately 3% less than those of nonstigmatized houses. Randall Bell, an appraiser in California, stated that well-recognized homicide events devalue property values by 15 to 35% after the incident (Umberger, 1999).

considered a situation in which consumers faced incomplete information. He empirically verified the existence of incomplete information among consumers by estimating differences in equilibrium prices before and after suppliers disclosed “bads” (disamenities) that were initially available to the public but not well recognized.

The approach adopted to examining the relationship between the hedonic model under incomplete information and hidden factors regarding the externality under complete information and consumers’ information on bads (in this case, stigmatized properties) differs significantly from those of Kask and Maani (1992) and Pope (2008a, b) in the following two respects. First, although each study considered a single bad, the study assumes a variety of hidden factors, such as the degree of externality under complete information and the types of prospective renter information that can differ by the type of stigmatizing event. This assumption makes the analysis more complex, but also more interesting. For example, the possibility is allowed that prospective renters recognize the existence of some stigmatized properties but cannot identify the event types. Therefore, the rental price of housing around stigmatized properties is affected by such prospective renters, for whom all possible event types will have a psychological impact. Secondly, assuming that a variety of hidden factors exist, a unique approach is proposed for examining the relationship. As shown later, F-tests of coefficients in the hedonic function between two different event types play a significant role in this exploration of hidden factors.

The structure of the paper is as follows. In the next section, the data used in this paper are presented. In section 3, hedonic models and the associated estimation results are then demonstrated. Section provides the results and the implications of the hidden factors behind the estimated hedonic functions. The final section provides some concluding remarks.

2.2. Data

Two types of data are used in this research. One is the stigmatized properties listed on the website Jikobukken.com[24] that describes stigmatizing events and times, and the property locations. The other data source is rental housing listed by the real estate agency Door

[24] The data of jikobukken.com was updated up to January 2011, and the record ended by at least October 2012. As of January 2013, the homepage of jikobukken.com (http://www.jikobukken.com) is removed and is merged to another website listing stigmatized property (http://www.oshimaland.co.jp) . The data listed in jikobukken.com used in this research is available upon request.

Chintai,[25] which describes rental prices offered and various housing characteristics.

Stigmatized properties

To our knowledge, no complete or official data are available on stigmatized properties in Japan or elsewhere. Although Japanese law requires housing suppliers to disclose stigmatizing events to prospective renters of these properties, the suppliers rarely provide such information at the beginning of negotiations with transactional partners or when they post descriptions of the properties on real estate agency websites. Rather, in most cases, the suppliers disclose stigmatizing events to prospective renters immediately before the renters sign a lease contract. One of the possible reasons for this practice is that property owners having had a stigmatizing event among their properties assets are concerned that potential customers might learn that a stigmatized property is located within the apartment building of interest, causing them to be reluctant to move into that building.

The data on stigmatized properties used in this paper were obtained from Jikobukken.com, a website that provides information on stigmatized properties in Japan, based on existing records and on information provided by the public. Consequently, the stigmatizing events reported on Jikobukken.com are not comprehensive and are recorded only if third parties have recognized the events. In this sense, well-known events or those that are easily revealed are more likely to be recorded on Jikobukken.com. Therefore, if an externality is present, it will be more likely to be recorded if it is large in this data set relative to other stigmatized properties for which information may have been withheld from the public.

The data include descriptions of the stigmatizing events, dates of the events, and addresses where the events took place. Events are categorized into five groups: discovery of a body, death by fire, suicide, homicide, and others. The events categorized in the "others" group included many unknown types of events and ones that had occurred before the present buildings had been constructed; as a result, they were excluded from the following regression analyses. The largest number of events was recorded for death by fire, accounting for 308 cases, followed by murder (260 cases), suicide (193 cases), and the discovery of a body (189 cases). The years when the events took place ranged from 1954 to 2011, with more than 80% of the events happening after 2005, whereas only one event was observed in 2011.

[25] http://chintai.door.ac/

Figure 2.1 shows spatial scatter plots of stigmatized properties in Tokyo Prefecture as recorded on Jikobukken.com. Many of the recorded events were observed within the 23 wards of Tokyo, the area making up the core of Tokyo Prefecture. Moving to the west of Tokyo Prefecture, an area that is less densely populated, the number of data points becomes smaller. Figure 2.2, which takes into account the number of housing units, illustrates the density of events by ward (number of events divided by 1,000 housing units). The figure illustrates the high propensity for stigmatized events in the 23 wards of Tokyo, even after controlling for the number of housing units.

Rental housing

Samples of rental housing in Tokyo Prefecture were collected between November 2011 and July 2012 from the rental real estate agency Door Chintai. After removing outlying rental price observations above the 99th percentile and below the 1st percentile, there were 132,268 observations in total. The data included rental prices as well as housing characteristics, namely, address, floor area, number of bedrooms, floor level, number of stories in a building, years since building completion, time to the closest train station by walking, building type, and building structure.[26] Definitions of the variables are presented in table 2.1, and their basic statistics are shown in table 2.2.

Using the addresses of properties listed on Door Chintai and Jikobukken.com, the distances between rental housing and stigmatized properties were computed based on the Geocoding Information System (GIS) provided by the Center for Spatial Information Science (CSIS),[27] from which we obtained the distance to the closest stigmatized properties, *Distance*, and the number of stigmatized properties within a certain range from rental housing, *#Events*.

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[26] Note that the rental prices observed for Door Chintai are available in the housing market; thus, they are not transactional prices, but are prices offered by property owners. One significant concern when conducting research using listed sale prices is that sale prices tend to be volatile across time and that some gaps generally exist between listed sale prices and transaction prices. However, housing rental prices change gradually over time compared with sale prices. This is because the rental price reflects the quality of housing services, the location, and the environment, which require a longer period to adjust, whereas sale prices reflect not only the quality of the property, but also expectations of the future: the theoretical sale price is the expected discounted value of rental revenue in the future. In this sense, using rental housing enabled us to avoid problems associated with volatility and expectations of the future and to focus on the quality of housing services and the environment, although it would have been ideal to have explicit information about the transactional rental prices.

[27] The CSIS is located at Tokyo University (http://www.csis.u-tokyo.ac.jp/japanese/index.html).

The geocoding of CSIS tracks the accuracy of the address up to the block level.[28] Consequently, distances between rental housing units and their closest stigmatized properties took values of zero if they were located in the same block, accounting for 1,348 rental housing units. By matching the addresses of these two data sets with the building level, there were 198 rental housing units located within buildings having stigmatized properties. We fond one stigmatized property in the rental housing data and excluded it from the samples.

2.3. Empirical Models

Empirical models

The final versions of the hedonic models used are complex, with many interaction terms between variables. The simple model is as follows:

$$\ln(Rent/ft2)_i = \boldsymbol{\alpha}_1\mathbf{V}_i + \boldsymbol{\alpha}_2\mathbf{X}_i + \varepsilon_i$$

$$\boldsymbol{\alpha}_1 = [\alpha_{Dis} \quad \alpha_{Bld} \quad \alpha_{Blk} \quad \alpha_{Age}], \quad \mathbf{V}_i = \begin{bmatrix} \ln(Distance+1)_i \\ Building_i \\ Block_i \\ \ln(EventAge) \end{bmatrix}. \tag{2.1}$$

Here, $\ln(Rent/ft2)_i$ is the natural logarithmic value of a rental price per square foot of housing i, $\mathbf{V}_i$ is a column vector of variables measuring the effects of the externality, $\boldsymbol{\alpha}_1$ is a row vector of coefficients for these variables, $\mathbf{X}_i$ is a column vector of control variables of the characteristics of housing i, $\boldsymbol{\alpha}_2$ is a row vector of coefficients for the control variables, and ε_i is an error term. In the specification of model (2.1), $\mathbf{V}_i$ contains four variables that measure the externality of a stigmatized property: 1) $\ln(Distance+1)_i$ is the natural logarithmic value of 1 plus the distance from housing i to its closest stigmatized property in feet. 2) $Building_i$ and 3) $Block_i$ are dummy variables indicating housing i located in the building and block, respectively, containing the stigmatized property. Because housing samples that take values of

[28] Unlike western addresses, Japanese addresses begin with the largest geographical entities. For instance, the address of the Tokyo Metropolitan Government Office Building is "Tokyo-to, Sinjyuku-ku, Nishi-Sinjyuku, 2-8-1," where "Tokyo-to" is the prefecture, "Sinjyuku-ku" is the city or ward, "Nishi-Sinjyuku, 2" is the city district, "8" is the block area, and "1" is the building number. If multiple housing units are in one building, room numbers are followed by the building number to express the address of the unit.

1 for $Building_i$ also assign values of 1 for $Block_i$, the coefficient for $Building_i$, α_{Bld}, reflects the difference in rental prices between housing in buildings having stigmatized property and other housing in the same block. 4) $EventAge_i$ is the number of years that have passed since the occurrence of the stigmatizing event closest to housing i. If the stigma of events decreases over time, the coefficient for $EventAge_i$ is expected to be positive.

The control variables, $\mathbf{X}_i$, include the variables described in table 2.2, such as the time to the closest train station, floor level, floor space, number of bedrooms, total number of stories in the building, year of building completion, and dummy variables for building types and structures. Dummy variables are included for train stations, with 1 assigned if the station is the closest to housing i and zero otherwise. All continuous control variables are converted into natural logarithmic values and their squared values are also included in $\mathbf{X}_i$.[29]

As can be seen in equation (2.1), the model is constructed to capture the externality on the housing rental price of the closest stigmatized property. However, it is possible that the rental prices are also influenced by other surrounding stigmatized properties. To control for the effect of having multiple stigmatizing sites close to housing i, the natural logarithmic value of $\#Events_i$, the number of stigmatized properties within a certain range from housing i, and its squared value are also included in $\mathbf{X}_i$.

The primary interest is in the coefficient for $Building_i$, α_{Bld}, which was expected to show the greatest externality among three variables, $\ln(Distance + 1)_i$, $Building_i$, and $Block_i$. If no externality exists within the building, it is unlikely that we would observe an externality outside the building. However, their coefficients may also reflect some indirect effects because of the existence of the stigmatized property. For instance, stigmatizing events may have a positive influence on neighboring housing values by inducing an improvement in facilities or security systems, characteristics that are omitted from the control variables, $\mathbf{X}_i$. In addition, because of the small number of observations for rental housing located in buildings containing stigmatized

[29] Committees suggest that effects of multiple stigmatized properties with different types of incidences should be addressed in the model, assuming that prospective renters may have some expectation about the probability of having stigmatized properties in the neighborhood without knowing where they exactly are located. The current hedonic model includes the total number of stigmatized properties within a certain range from each housing as an independent variable to control the effect of having multiple stigmatized properties in the neighborhood to some extent. However, for the future research, using the crime rate and numbers of stigmatized properties by event types in the neighborhood may help to address degrees of expectations and stigma by potential renters that may differ among the types of event.

properties, the coefficient for $Building_i$, α_{Bld}, may not be significant, whereas a significant externality might be observed for other variables, $\ln(Distance + 1)_i$ and $Block_i$.

Effects of the externality in terms of distance to the closest stigmatizing event are captured by the coefficient for $\ln(Distance + 1)_i$. If a spatial externality exists because of a stigmatized property, the coefficient is expected to have a positive sign because the rental price should increase as housing is located farther from the site.

The coefficient for $Block_i$, α_{Blk}, in model (2.1), is not easy to interpret because, by including $\ln(Distance + 1)_i$ as an explanatory variable, the coefficient indicates the difference in rental prices between housing in blocks with stigmatizing events and housing outside the areas that are assumed to be located at zero distance from the stigmatized property. The simplest remedy for this problem is to exclude $\ln(Distance + 1)_i$ from model (2.1) so that differences in rental prices between inside and outside the block area can be estimated directly by looking at the coefficients for $Block_i$. This corresponds to the model in which vectors $\boldsymbol{\alpha}_1$ and $\mathbf{V}_i$ are specified as follows:

$$\boldsymbol{\alpha}_1 = [\beta_{Bld} \quad \beta_{Blk} \quad \beta_{Age}], \quad \mathbf{V}_i = \begin{bmatrix} Building_i \\ Block_i \\ \ln(EventAge)_i \end{bmatrix}. \tag{2.2}$$

In models (2.1) and (2.2), the externality captured by the coefficients for $\ln(Distance + 1)_i$, $Building_i$, and $Block_i$ are assumed to be constant over time. In other words, these coefficients evaluate mean effects because of the existence of stigmatized properties, regardless of when the events occurred. The following models are extensions of models (2.1) and (2.2), which alleviate the externality by taking into consideration the possibility that prospective renters not only are aware of the presence of a stigmatized property, but also know the time of the event:

$$\begin{cases} \boldsymbol{\alpha}_1 = [\gamma_0 \quad \gamma_{Age} \quad \gamma_{Bld} \quad \gamma_{Bld*Age} \quad \gamma_{Blk} \quad \gamma_{Blk*Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \end{cases}, \tag{2.3}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\delta_0 \quad \delta_{Age} \quad \delta_{Dis} \quad \delta_{Dis*Age} \quad \delta_{Bld} \quad \delta_{Bld*Age} \quad \delta_{Blk} \quad \delta_{Blk*Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ \ln(Distance+1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \end{cases} . \tag{2.4}$$

To gain a clear sense of these equations, take the derivative of the rental price function of model (2.3) with respect to $\ln(EventAge)_i$, that is:

$$\frac{\partial \ln(Rent/ft2)_i}{\partial \ln(EventAge)_i} = \gamma_{Age} + \gamma_{Bld*Age} Building_i + \gamma_{Blk*Age} Block_i. \tag{2.5}$$

The left side of equation (2.5) shows the elasticity of the rental price with respect to the number of years that have passed since the stigmatizing event. Consequently, $\gamma_{Blk*Age}$ indicates the percentage increase in the rental price of housing located in a block with a stigmatized property as 1% more time passes after the event. If time alleviates the stigma of events within that block, then $\gamma_{Blk*Age}$ should take a positive value. Furthermore, if property owners enhance their building security yearly after the occurrence of a stigmatizing event within the same block, the rental prices should increase after the security measures are implemented, which would also positively affect $\gamma_{Blk*Age}$. Conversely, if security measures are implemented immediately after the event, this does not affect $\gamma_{Blk*Age}$, but rather, makes γ_{Blk} positive. To clarify this point, let us take a derivative of the rental price function of model (2.3) with respect to $Block_i$:

$$\frac{\partial \ln(Rent/ft2)_i}{\partial Block_i} = \gamma_{Blk} + \gamma_{Blk*Age} \ln(EventAge)_i. \tag{2.6}$$

When $EventAge_i$ is equal to 1, $\ln(EventAge)_i$ is zero, indicating that γ_{Blk} in equation (2.6) is the externality of a stigmatized property within that block 1 year after the event. If the improvement in housing quality in the first year after the stigmatizing event has a great enough benefit to prospective renters to compensate for the stigma, γ_{Blk} could be greater than zero.

The rental price functions are estimated based on models (2.1) to (2.4), assuming that the extent of the externality could differ by the event type. To see these differences, $\ln(Distance+1)_i$, $Building_i$, $Block_i$ and $\ln(EventAge)_i$ are multiplied by a dummy variable for each event type: $Discovery_i$ (discovery of a body), $Fire_i$ (death by fire), $Suicide_i$ (suicide), and $Homicide_i$ (homicide). Let D, F, S, and H refer to the discovery of a body, a death by fire, a suicide, and a homicide, respectively, and let a column vector be defined as $\mathbf{Type}_i \equiv [Discovery_i \quad Fire_i \quad Suicide_i \quad Homicide_i]'$. This yields the final version of the empirical models, with the following specifications of vectors $\boldsymbol{\alpha}_1$ and $\mathbf{V}_i$, from (2.7) to (2.10), which correspond to the extensions of models (2.2), (2.1), (2.3), and (2.4), respectively:

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\alpha} \quad \boldsymbol{\alpha}_{Bld} \quad \boldsymbol{\alpha}_{Blk}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes [\mathbf{Type}_i]' \end{cases} \tag{2.7}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\beta}_{Dis} \quad \boldsymbol{\beta}_{Bld} \quad \boldsymbol{\beta}_{Blk}] \\ \mathbf{V}_i = \begin{bmatrix} \ln(Distance + 1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes [\mathbf{Type}_i]' \end{cases} \tag{2.8}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\gamma} \quad \boldsymbol{\gamma}_{Age} \quad \boldsymbol{\gamma}_{Bld} \quad \boldsymbol{\gamma}_{Bld*Age} \quad \boldsymbol{\gamma}_{Blk} \quad \boldsymbol{\gamma}_{Blk*Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \otimes [\mathbf{Type}_i] \end{cases}, \tag{2.9}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\delta} \quad \boldsymbol{\delta}_{Age} \quad \boldsymbol{\delta}_{Dis} \quad \boldsymbol{\delta}_{Dis*Age} \quad \boldsymbol{\delta}_{Bld} \quad \boldsymbol{\delta}_{Bld*Age} \quad \boldsymbol{\delta}_{Blk} \quad \boldsymbol{\delta}_{Blk*Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ \ln(Distance + 1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \otimes [\mathbf{Type}_i] \end{cases}. \tag{2.10}$$

Here, the boldfaced parameters in brackets are (1 × 4) vectors containing coefficients for four event types, namely, $\boldsymbol{\alpha}_{Bld} \equiv [\alpha_{Bld}^D \quad \alpha_{Bld}^F \quad \alpha_{Bld}^S \quad \alpha_{Bld}^H]$. Note that restrictions are imposed on a vector of coefficients, $\boldsymbol{\delta}$, in model (10) such that $\delta^D = \delta^F = \delta^S = \delta^H$ because otherwise, the effects of $\ln(Distance + 1)_i$, δ_{Dis}^k, where $k \in \{D, F, S, H\}$, would be subtracted by the effects captured in δ^k, which is the mean effect of each event type on the area outside the block with the stigmatized property. If different parameters are used in $\boldsymbol{\delta}$, the effect of the externality in δ_{Dis}^k will be underestimated for event type k, which has a high spatial externality, because a large mean externality effect, δ^k, absolves the effects on δ_{Dis}^k.

Using models (2.7) to (2.10), each rental price function is estimayted with different sample sizes; estimations are restricted to rental housing units located within 0.2, 0.3, and 0.5 miles from the observed stigmatized properties, for which the number of stigmatized properties within 0.2, 0.3, and 0.5 miles from housing i are used as $\#Events_i$ in $\mathbf{X}_i$, respectively. Estimations are conducted with different restricted sizes of data sets mainly for two reasons. First, although it is preferable to use a larger sample size to have more degrees of freedom, the spatial externality, if this exists, might be captured only within a certain distance from the stigmatized properties. If one were to include many samples located too far from the stigmatized properties, significant effects of $\ln(Distance + 1)_i$, might not be found, even if the externality existed within a limited range from the sites.

Secondly, as shown in figure 2.1, some stigmatized properties are highly clustered, whereas others are sparse. In a district with highly clustered stigmatized properties, the area having the closest stigmatized properties in common is small. In such districts, the average distance to the closest stigmatized property would be nearby. If a correlation exists between the average distance to the closest stigmatized property and a rental price that is not controlled by $\mathbf{X}_i$, then the estimated coefficients for $\ln(Distance + 1)_i$ would suffer from an endogeneity problem, inducing biased estimates. In this regard, although some variables in $\mathbf{X}_i$, such as #Events, Time, and station dummies, are expected to resolve the issue of endogeneity, estimations with a restricted number of samples may give more accurate estimates of the distance to the closest stigmatized property, whereas the degrees of freedom are smaller with a smaller sample size. Concerning these two sample selection problems, no attempt was made to elaborate on the coefficients of $\ln(Distance + 1)_i$. Instead, attention was directed to the signs, significance, and tendencies of magnitudes of the coefficients of $\ln(Distance + 1)_i$ across different sample sizes and check the robustness of other variables.

2.4. Estimation Results

Table 2.3 describes the estimation results for models (2.7) and (2.8). Each column uses samples lying within a certain range (0.2, 0.3, or 0.5 miles) of the stigmatized properties. Based on the number of observations in table 2.3, the sample size decreases from 92,436 to 60,774 and then to 35,545 as the range is restricted from 0.5 to 0.3 and then to 0.2 miles.

Examine the coefficients for $Building_i$, $\boldsymbol{\alpha}_{Bld}$, and $Block_i$, $\boldsymbol{\alpha}_{Blk}$, in model (2.7). The estimation results are shown in columns [3-1] to [3-3]. Regarding $Building_i$, the coefficients are negative and significant for the event types death by fire and homicide; specifically, the rental price of a housing unit in a building where an individual died in a fire is 2.2 to 3.4% lower than the rental price of other housing in the same block, and the rental price decreases by 5.3 to

5.6% in the case of a homicide. In contrast, the coefficients of $Block_i$ for death by fire, α^F_{Blk}, and homicide, α^H_{Blk}, are positive and significant. The only event type showing a negative effect for $Block_i$ is suicide; the rental price of housing in a block containing a property stigmatized by suicide is 3.8 to 4.0% lower than the rental price of housing located outside that block.

In columns [3-4] to [3-6] of table 2.3, all coefficients for $\ln(Distance + 1)_i$ have a positive effect on the rental price, whereas these magnitudes and significances vary by event type as well as by sample size. The coefficients of death by fire, α^F_{Dis}, are positive and significant in all estimations across the different sample sizes. In contrast, the discovery of a body does not have a significant effect on the externality for either $\ln(Distance + 1)_i$ or $Building_i$ and $Block_i$.

Recall that stigmatizing events are recorded on Jikobukken.com only when third parties have observed these facts. These events are revealed through media reports and by members of the public. Among the four event types, death by fire and homicide are the most likely to be recognized by large numbers of people. For a death by fire, members of the neighborhood can easily recognize the incident by observing or hearing firefighters in the area. This may reflect the fact that the externality of death by fire reaches a wider range of people because information about such an event is easily accessible compared with information about other event types. In addition, a fire does not spread beyond the block because each block is surrounded by streets. When an individual dies in a fire, property owners and residents in that block may realize the risk and move to install fire prevention devices. This is one possible explanation for the positive signs observed for $Block_i$, α^F_{Blk}.

This scenario applies in the case of homicide as well. The event of a homicide is more likely to be widely reported by the media than is any other event type, and a large number of people will be aware of the event. Consequently, as shown in the results, the rental price of housing in a building where a homicide was committed declines sharply. In contrast, the rental price of housing in that block increases after a homicide, suggesting that managers of the surrounding buildings might facilitate the installation of security systems to improve the quality of housing enough to compensate for the potentially stigmatizing event.

Regarding $\ln(EventAge)_i$, the signs of the coefficients and their significance values are not consistent. Although the time since the event is expected to have a positive influence on the rental price, only the coefficients for suicide, α^F_{Dis}, consistently show positive signs. Using models (2.9) and (2.10), the effects are examined on the externality of interactions between $\ln(EventAge)_i$ and other variables, such as $Building_i$, $Block_i$, and $\ln(Distance + 1)_i$. The estimation results are shown in table 2.4.

According to the results of model (2.9) presented in columns [4-1] to [4-3], the only event type consistently having a significant result for γ^k_{Bld} and $\gamma^k_{Bld*Age}$ is homicide. One year after a homicide incident in the same building, the housing rental price is lower by 19.1 to 21.0% compared with the rental price of housing in the same block, whereas the rental price recovers by 8.04 to 8.94% as the same amount of time passes after an event. In contrast, $Fire_i$ does not have a significant effect for γ^F_{Bld} and $\gamma^F_{Bld*Age}$, whereas a negative externality of $Fire_i$ was observed in the previous estimations. The primary reason for this observation is the presence of multicollinearity. Another possibility is that prospective renters are unaware of when an individual might have died in a fire, in which case the true specification for the empirical model for death by fire is to exclude the interaction between $Fire_i$ and $\ln(EventAge)_i$.

Regarding $Block_i$, the discovery of a body and suicide are the only event types whose coefficients, γ^k_{Blk} and $\gamma^k_{Blk*Age}$, are significant; the rental price decreases by 6.4 to 6.5% and 11.8 to 13.1% in the first year after the discovery of a body and a suicide, respectively, and it recovers by 4.28 to 4.56% and 3.68 to 4.21%, respectively, as the same amount of time passes after an event. For example, if the rental price 5 years after an event is \$1,000.0, then it will become \$1,008.0 to \$1,008.9 10 years after the event (an increase of 0.80 to 0.89% as another 5 years pass). In contrast, the coefficients for γ^H_{Blk} show positive signs. In the preceding estimations, we suggest that security may be improved in housing in a block where a homicide was committed, thus increasing the rental value. Given that γ^H_{Blk} is positive but $\gamma^H_{Blk*Age}$ is not statistically different from zero, the estimation results imply that security systems are typically installed within the first year after a homicide.

In columns [4-4] to [4-6] in table 2.4, the coefficients for $\ln(Distance + 1)_i$, δ^k_{Dis}, are positive and significant for all event types, indicating that a spatial negative externality exists after the occurrence of an event of any type. The coefficients for $Fire_i$, δ^F_{Dis}, and $Homicide_i$, δ^H_{Dis}, and their significance levels in particular are greater than those for the other two event types. This is consistent with the intuition that these two event types are easily revealed and that their externalities are far reaching. Finally, the coefficient for $\ln(Distance + 1)_i \times \ln(EventAge)_i$, $\delta^k_{Dis*Age}$, has a negative sign for all event types, implying that the extent of the spatial externality diminishes over time.

2.5. Implications of the Hedonic Estimates Under Incomplete Information

The previous estimations detected the presence of an externality of stigmatized property. If prospective renters were fully informed about the stigmatized properties recorded on Jikobukken.com, and if other factors influencing the housing rental price were well controlled in the estimation, the estimated coefficients indicating the influence of stigmatized property would represent the implicit influence of such property on prospective renters under complete information, where prospective renters are fully informed of stigmatized properties via Jikobukken.com. However, the information on Jikobukken.com is not common knowledge, and only a portion of prospective renters are likely to recognize each stigmatized property listed. When prospective renters encounter imperfect information, the hedonic model under complete information may underestimate the implicit externality.

Although a small number of studies have examined how the hedonic model is interpreted under incomplete information, Pope (2008b) has provided intuitive explanation, including graphical demonstrations, regarding the relationship between the hedonic model and asymmetric information, in which suppliers have complete information on bads but consumers may have less information. Figure 2.3, which is taken from Pope (2008b), shows the possible bundle of equilibrium prices along with the quantity (or quality) of bads in the shaded area. If consumers are fully informed about bads, the equilibrium price will coincide with the envelope of minimum offers by suppliers, which will cause a decrease in the quantity of bads. On the contrary, if consumers possess no information on bads, the equilibrium price will be the envelope of maximum bids by consumers, which will be constant regardless of the quantity of bads. Between these envelopes, the equilibrium price given some quantity of bads can vary according to the fraction of consumers having information on the bads and the expectations of suppliers for that fraction. Intuitively, the path of the equilibrium price shifts downward as consumers become more informed.[30]

In this section, we investigate estimates of the hedonic rental price function under incomplete

[30] As Pope (2008b) mentions, the exact path of the equilibrium price has not been formally proved.

information to obtain possible interpretations of the hidden factors behind these estimates, such as on the externality under complete information and on the information about stigmatized properties that prospective renters possess. These hidden factors cannot be identified from a single coefficient, and few implications are obtained without imposing restrictions on these factors.

To see how few implications we could obtain, consider, for example, the coefficients for $Building_i$ for death by fire, α_{Bld}^{F}, in model (2.7), which range between -0.0342 and -0.0217. As discussed, even though all other factors were well controlled in the model, these estimates do not represent the externality under complete information. It is surprising that although these coefficients are significantly different from zero, one cannot exclude the possibility that no significant externality of death by fire exists under complete information. This could be true when prospective renters recognize the presence of stigmatized properties but cannot identify the event as a death by fire and suspect that something worse may have happened on the premises.

For another example, consider the coefficients for $Building_i$ for discovery of a body, α_{Bld}^{D}, in model (2.7), which range from -0.0267 to -0.0221. Even when they are not statistically significant, the possibility cannot be excluded that the discovery of a body would have a significant externality under complete information. This is because properties stigmatized by the discovery of a body could be difficult for prospective renters to recognize, which attenuates the effect of the presence of these properties.

To clarify these points, the relationships between incomplete information and coefficients of the hedonic model are discussed in the following subsections. First, the coefficients of the hedonic model are decomposed under several assumptions, enabling examination of the relationship between the estimated coefficients and their hidden factors. Then, three cases are discussed in which reasonable restrictions are imposed on some hidden factors, and examine the interpretation of unrestricted factors. Finally, the analytical frameworks of these cases are applied to the estimation results provided in the previous section.

Decomposition of coefficients of the hedonic model

We consider four submarkets of rental housing located at a fixed distance from the closest stigmatized properties. Each submarket deals with rental housing whose closest stigmatized properties are of the same event type, $k \in K \equiv \{D, F, S, H\}$. Let J^k be a set of rental properties whose closest stigmatized properties are of event type $k \in K$, with an element of J^k denoted by j^k; then let I^k be a set of prospective renters of housing J^k. In addition, let S^k be a set of stigmatized properties whose event type is k, and let s^k be an element of S^k.

A prospective renter, $i \in I^k$, has one of the following three kinds of information about each stigmatized property, $s^k \in S^k$: (A) prospective renter i recognizes the presence of the stigmatized property and also identifies its event type k, (B) prospective renter i recognizes the presence of the stigmatized property but does not know the event type k, or (C) prospective renter i does not recognize the presence of the stigmatized property.

If all prospective renters in I^k are expected to have information (A) on all $s^k \in S^k$ (i.e., all prospective renters in the housing submarket of J^k are expected to recognize all stigmatized properties in S^k and their event type k), then the decrease in the offered rental price of J^k resulting from the presence of stigmatized properties S^k is equal to the influence of event type k under complete information. On the contrary, if all prospective renters in I^k are expected to have information (C) on all $s^k \in S^k$ for all $k \in K$ (i.e., no prospective renter knows the presence of any stigmatized property), then the offered rental prices in the housing market of J^k for all $k \in K$ will not be affected by stigmatized properties and are thus the same.

Figures 2.4 and 2.5 demonstrate how the externality under complete information and the expected possibility of prospective renters in I^k having information (A), (B), and (C) affects the offered rental price of J^k.

In figure 2.4, A, B, and C are the demand curves when all the prospective renters in I^k have information (A), (B), and (C) on all $s^k \in S^k$, respectively. The heavy line in figure 2.5 describes one possible demand curve that property owners of J^k expect to encounter, and R^k is the offered rental price at which the expected demand curve intersects the supply curve.[31] Figure 2.3, from Pope (2008b), shows the path of the equilibrium price along with the quantity of bads, whereas figures 2.4 and 2.5 demonstrate the demand and supply curves given a fixed quantity of bads (in this case, the distance to the closest stigmatized property).

Next, the coefficient of the hedonic model is decomposed to account for the externality. Let τ_A^k

[31] The supply curve is vertical because we are considering the short-term housing market, where the temporal housing stock is fixed.

be the absolute degree of externality of stigmatized property j^k under complete information, let τ_B^k be the absolute degree of externality when prospective renters recognize the existence of the stigmatized property but cannot identify its event type k, and let τ_C^k be the absolute degree of externality when prospective renters do not recognize the existence of the stigmatized property. Consider the following decomposition of a hedonic estimate regarding the externality:

$$|\alpha^k| = \theta_A^k \tau_A^k + \theta_B^k \tau_B^k + \theta_C^k \tau_C^k. \tag{2.11}$$

where parameters θ_A^k, θ_B^k and θ_C^k are defined as weights of τ_A^k, τ_B^k and τ_C^k such that the sum of their products equals the absolute value of the estimated coefficient. Here, $\tau_C^k = 0$ because no externality exists if the stigmatized property j^k is not recognized. Furthermore, it is assumed that prospective renters suspect all event types equally when they have information (B) on the stigmatized properties, implying that $\tau_B^k = \tilde{\tau}$ for all $k \in K$, where $\tilde{\tau}$ is the mean externality of all event types. By denoting τ_A^k and τ_B^k by τ^k and $\tilde{\tau}$, respectively, the decomposition of the hedonic estimate may be presented as:

$$|\alpha^k| = \theta_A^k \tau^k + \theta_B^k \tilde{\tau}. \tag{2.12}$$

Greater θ_A^k and θ_B^k imply, respectively, more prospective renters in I^k having information (A) and (B), shifting the expected demand curve from C closer to A and B in figures 2.4 and 2.5. Therefore, it is possible to consider θ_A^k and θ_B^k as I^k contributing information (A) and (B), respectively, to the position of the expected demand curve. The increase in θ_A^k and θ_B^k reduces the offered rental price, as seen in figures 2.4 and 2.5, which corresponds to the downward shift in the equilibrium price in figure 2.3 as the incompleteness of information increases.

Finally, note two points regarding the hidden parameters in equation (2.12). First, the fact that θ_A^k is zero does not necessarily mean that no prospective renters have information (A) on any $s^k \in S^k$; in other words, even if θ_A^k is zero, it is possible to have a number of prospective renters who identify event type k of some $s^k \in S^k$. This is because a demand curve in the housing market of J^k is determined endogenously in such a way that prospective renters intend to avoid renting housing nearby recognizable stigmatized properties whose event type might have a significant negative psychological impact on them. In this sense, in addition to the incomplete information, the estimated coefficient may underestimate the implicit influence of stigmatized property because of the endogeneity such that prospective renters intend to avoid areas they recognize as stigmatized properties, whereas they may live around properties they do not recognize as being stigmatized.

Secondly, hedonic rental price functions in our estimations use natural logarithmic values for the independent variables. This means that the coefficient α^k indicates the percentage change in the rental price when a variable increases marginally; that is, $|\alpha^k| = \left(R_C^k - R^k\right)/R_C^k$. Accordingly, τ^k and $\tilde{\tau}$ are characterized as $\tau^k = \left(R_C^k - R_A^k\right)/R_C^k$ and $\tilde{\tau} = \left(R_C^k - R_B^k\right)/R_C^k$.

Implications of under three cases

In equation (2.12), there are four unknown parameters, but with only one given only a single value, α^k, from the estimation. If either θ_A^k or τ^k is zero, the sign of the other parameter is no longer known, as for θ_B^k and $\tilde{\tau}$. Therefore, when α^k is not statistically different from zero, nothing can be concluded about these hidden parameters unless some assumptions are imposed. Now, consider three cases with different restrictions on some parameters and examine their implications for unrestricted parameters. All proofs are provided in the Appendix C.

Case (a): $\theta_B^k = 0$ for all k.

In case (a), it is assumed that prospective renters do not recognize a stigmatized event whose event type is unknown. In other words, prospective renters recognize properties as stigmatized only when they identify their event types. This is the case when people learn about stigmatized properties only through media reports that describe the events in detail. In this situation, the following relationship is derived between the parameters and the estimated coefficients:

$\theta_A^k > 0,\ \tau^k > 0$ if and only if $|\alpha^k| > 0$.

When the coefficient of event type k is strictly positive, it implies that property owners of J^k expect some prospective renters in I^k to identify event type k in their closest stigmatized properties; furthermore, event type k has a negative externality under complete information.

Case (b): $\tau^k = \tau^l$ for all k and l.

The second case assumes that all stigmatizing event types have the same effect. This assumption appears strict because the psychological impact of the stigmatizing event seems to differ according to the manner in which the event occurs. However, if prospective renters are concerned, especially about the fact that someone in the neighborhood has died, regardless of how the incident happened, then this assumption statistically represents the reality. In this circumstance, the following relationships are implied:

$\theta_A^k + \theta_B^k > 0$ and $\tau^k = \tau^l = \tilde{\tau} > 0$ for all l if and only if $|\alpha^k| > 0$.

If $\exists m$ s.t. $|\alpha^m| > 0$, then $\theta_A^k + \theta_B^k = 0$ if and only if $|\alpha^k| = 0$.

If $\exists m$ s.t. $|\alpha^m| > 0$, then $\theta_A^k + \theta_B^k > \theta_A^l + \theta_B^l$ if and only if $|\alpha^k| > |\alpha^l|$.

The sum of θ_A^k and θ_B^k represents the contribution of prospective renters in I^k, who recognize the existence of the closest properties stigmatized by event type k; thus, a positive $|\alpha^k|$ implies that a number of prospective renters in I^k are aware of stigmatized properties of event type k. Furthermore, if some event type $m \neq k$ exists such that $|\alpha^m| > 0$, then $|\alpha^k|$ being zero implies that prospective renters in I^k do not contribute to the change in the offered rental price, whereas the externality under complete information is significant. Finally, if some event type m exists such that $|\alpha^m| > 0$, then $|\alpha^k| > |\alpha^l|$ implies that prospective renters who recognize the closest stigmatized properties have a greater contribution to the change in the offered price in the housing market of J^k relative to the housing market of J^l.

Case (c): $\theta_A^k = \theta_A(\tau^k)$ and $\theta_B^k = \theta_B(\theta_A^k)$,

$$\text{where} \begin{cases} -1 < \dfrac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k} < 0 & \text{if} \quad \theta_A^k \in (0, \theta_A(0)] \\ \dfrac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k} = 0 & \text{if} \quad \theta_A^k = 0 \\ \dfrac{\partial ln\theta_B(\theta_A^k)}{\partial ln\theta_A^k} < 0 & \text{if} \quad \theta_B^k \in (0, \theta_B(0)] \\ \dfrac{\partial ln\theta_B(\theta_A^k)}{\partial ln\theta_A^k} = 0 & \text{if} \quad \theta_B^k = 0 \end{cases}$$

In case (c), we assume that θ_A^k is a function of τ^k and θ_B^k is a function of θ_A^k. Under these conditions, θ_A^k and θ_B^k are determined solely by τ^k. First, it is assume that θ_A^k is a decreasing function of τ^k. This assumption recognizes the endogenous issue in which prospective renters intend to avoid neighbors renting stigmatized properties whose event type has a great psychological impact on them. Here, the elasticity of θ_A with respect to τ^k is assumed to be greater than -1, meaning that even if the extent of the externality under complete information were to double, θ_A^k would not decrease as low as half of its initial value. Secondly,

θ_B^k is assumed to be a decreasing function of θ_A^k, meaning that prospective renters in I^k are more likely to have information (B) when fewer prospective renters in I^k have information (A). From these assumptions, the following conditions are derived:

$\tau^k > \tau^l$, $\theta_A^k < \theta_A^l$ and $\theta_B^k \geq \theta_B^l$ if $|\alpha^k| > |\alpha^l|$.

$\tau^l = 0$ and $\theta_A^l = \theta_A(0)$ if $|\alpha^k| > |\alpha^l| = 0$.

If $\exists m$ s.t. $|\alpha^k| = |\alpha^l| > |\alpha^m| = 0,$ then $\tau^k = \tau^l > 0, \theta_A^k = \theta_A^l > 0$ and $\theta_B^k = \theta_B^l$.

If $\exists m$ s.t. $|\alpha^m| > |\alpha^k| = |\alpha^l| = 0,$ then $\tau^k = \tau^l = 0, \theta_A^k = \theta_A^l = \theta_A(0)$ and $\theta_B^k = \theta_B^l$.

If $\nexists m$ s.t. $|\alpha^m| > |\alpha^k| = |\alpha^l| > 0,$ then $\tau^k = \tau^l > 0, \theta_A^k = \theta_A^l$ and $\theta_B^k = \theta_B^l$.

Unlike in cases (a) and (b), the implications are obtained only by using the *F*-test to examine the difference in coefficients between two event types in case (c). If $|\alpha^k| > |\alpha^l|$, this ensures that the externality of event type k, τ^k, is greater than that of event type l, τ^l. In addition, under this condition, if $|\alpha^l|$ is zero, then no externality exists for event type l under complete information. On the other hand, if $|\alpha^l|$ is greater than zero, and if some event type exists whose coefficient is zero, then both θ_A^l and τ^l are greater than zero. Finally, consider $|\alpha^k| = |\alpha^l|$. If these values are greater than zero and some event type exists whose coefficient is zero, then all parameters between k and l are the same, whereas the degree of their externality under complete information is zero. On the other hand, if these values are zero and no event type exists whose coefficient has an absolute value greater than those of event types k and l, then the degree of the externality of event types k and l is greater than zero.

Application to the estimated results

Finally, the implications of the hidden parameters in equation (2.12) are examined based on the three cases described in the previous subsection by using the estimation results from columns [4-1] and [4-4] in table 2.4. To do this, *F*-tests are conducted first on the coefficients to determine the externality of a stigmatized property 1, 5, and 10 years after the event. The coefficients for the externality of the stigmatized property 1, 5, and 10 years after the event are computed by $\gamma_{Bld}^k + \gamma_{Bld*Age}^k \ln(\#years)$ and $\gamma_{Blk}^k + \gamma_{Blk*Age}^k \ln(\#years)$ from estimates for model (2.9) for Building and Block, respectively, and $\delta_{Dis}^k + \delta_{Dis\square Age}^k \ln(\#years)$ from model (2.10) for ln(Distance + 1). For each of these three variables, *F*-tests are then conducted on the coefficients for every combination of two event types, whose null hypothesis is that coefficients of the two event types are equal.

Table 2.5 shows *P*-values of the *F*-tests and *t*-tests for the coefficients for Building, Block, and ln(Distance + 1) 1, 5, and 10 years after the event for each event type. The null hypotheses on *F*-tests and *t*-tests are rejected by using two-sided tests and a 5% significance level. Here, these tests were adjusted for coefficients showing unexpected signs, indicating the positive externality of stigmatized property. First, absolute values of the coefficients with unexpected signs are set to zero, meaning that no externality is assumed where the coefficient shows a positive externality. Secondly, the *F*-test between two coefficients, one with an unexpected sign and the other with an expected sign, is discarded and the difference between these coefficients is evaluated based on the t-test for the one having the expected sign. The difference between two coefficients whose signs are both unexpected is set at zero. According to these criteria, coefficients showing a significant externality and combinations of two coefficients showing significant differences are re-marked with plus signs (+) in table 2.5.

Finally, the implications of hidden parameters among four event types for the three cases, (a), (b), and (c), are shown in table 2.6. The shaded text in the table indicates the assumptions made in each case. The results for each case will be reviewed.

Case (a): It is assumed that θ_B^k is zero for all event types. In this case, under complete information, homicide has a significant negative externality within the building 1 and 5 years after the incident, and prospective renters in I^H, having information (A), contribute to reducing the offered rental price. Nothing can be concluded about θ_A^k and τ^k for the other event types because $|\alpha^k|$ being zero means that either θ_A^k or τ^k is zero; however, we do not know which parameter takes the value of zero. Ten years after an event, nothing can be said about θ_A^k and τ^k for any event type. This is because the impact of homicide fades over time and prospective renters are not expected to remember, or are no longer concerned about, stigmatizing events that happened 10 years ago.

Regarding the Block, suicide has a significant externality even 10 years after the event. This implies that some prospective renters are still expected to identify the event type that stigmatized the property if a suicide occurred within the last 10 years in the block where their prospective rental housing is located, and they are reluctant to live in the neighborhood. For ln(Distance +

1), all event types have a significant spatial externality under complete information in the first year after an event. However, in 5 years, the evidence of a significant impact remains only for the discovery of a body and a homicide, and no event type leaves evidence of an externality 10 years after an event.

There are some counterintuitive results. For example, although the results suggest evidence of a spatial externality under complete information for all event types, such strong evidence is not obtained within the block and the building, where the degree of externality is expected to be greater. Furthermore, although a strong and long-lasting externality of suicide is observed within the block, its negative externality is not observed within the building. One possible reason for these results is the small sample size for rental housing located within buildings and blocks that contain stigmatized properties; for instance, there were only 198 rental units in buildings containing stigmatized properties. When using dummy variables for event types and the interaction terms between these dummy variables and the number of years since an event, the estimation suffers from fewer degrees of freedom as well as multicollinearity. Another possibility is the endogeneity attributable to omitted variables, as discussed in the previous section, whereby stigmatizing events may induce an indirect positive externality on the quality of housing in the neighborhood as security systems and facilities are implemented.

Case (b): This case assumes that all event types have the same degree of externality under complete information. One and 5 years after an event, property owners of J^H expect that some prospective renters in I^H will recognize the presence of the closest stigmatized properties; thus, they reduce their offered price. On the contrary, other event types do not have an influence on the offered rental price within the building, implying that in cases of the discovery of a body, death by fire, and suicide, property owners do not expect many prospective renters to know about the closest stigmatized properties. Ten years after an event, no event type k is recognizable by prospective renters in I^k.

Within one block of a stigmatized property, numerous prospective renters are expected to recognize suicide for more than 10 years, whereas there is no evidence of prospective renters recognizing the presence of other event types. Regarding the spatial externality, ln(Distance + 1), all event types are expected to be easily recognizable 1 year after the event. An F-test shows that homicide, death by fire, and suicide have the same externality effect under complete information, and these event types are greater than the effect of the discovery of a body. Five years after an event, however, the significance of the effect remains only for homicide and for the discovery of a body, and it disappears for all event types after 10 years. These results indicate that prospective renters recognize fewer stigmatizing events as time passes.

Case (c): The last case assumes, first, that prospective renters intend to avoid living near stigmatizing events that have a greater psychological impact. Secondly, the elasticity of the externality of θ_B^k is greater than minus one. Finally, the greater the possibility of prospective renters identifying the event type, the smaller the possibility that they will recognize but not be able to identify the event type.

For the first 5 years after an incident within a building, only homicide has a negative externality under complete information, whereas other event types have no significant externality. By assumption, the fraction of prospective renters in I^k having information (A) is strictly smaller than the fraction having information about other event types. Within that block, on the other hand, suicide is the only event type showing a negative externality under complete information, and the effect persists even 10 years after an incident. Regarding the spatial externality, the discovery of a body has the smallest externality under complete information. It is interesting that it is not clear whether the spatial externality of the discovery of a body is significant, unlike in cases (a) and (b). Furthermore, nothing can be interpreted anything 5 years after the incident because no combination of coefficients between two event types is significantly different.

2.6. Conclusion

Housing suppliers are not obligated to disclose the presence of stigmatized properties as long as no incident has taken place on the transactional properties. However, if a prospective renter is aware of a stigmatized property nearby rental housing in which he or she is interested, the renter may not want to rent that unit unless the rental price is low enough to compensate for his or her discomfort with the event. Consequently, housing suppliers determine the offered rental price based not only on the effect of nearby stigmatizing events, but also on the information that their prospective renters may have about these stigmatized properties.

When data on rental housing and stigmatized properties recorded in Tokyo, Japan, were used, the hedonic approach revealed the presence of a negative externality of stigmatized properties. The estimation results showed that the rental price decreases by 5.3 to 5.6% relative to the rental price of other housing in the same block if the building has had a homicide and by 2.2 to 3.5% in the case of a death by fire. In contrast, there are no significant effects on properties stigmatized by the other two event types. It is surprising that one year after a homicide, the rental price of housing within the same building is 19.1 to 21.0% lower than the rental price of other housing in the same block, although it recovers gradually over time.

Regarding the spatial externality, there were significant positive relationships between the offered rental price and the distance from the closest stigmatized property, implying that the offered rental price decreases the closer the housing is to a stigmatized property. The spatial externalities become weaker as time passes after an incident. Among the four event types, properties stigmatized by death, fire and homicide have greater spatial externalities than the other two types.

Since the stigmatized properties in the dataset are not common knowledge, these estimates using the hedonic model do not represent the implicit externality under complete information, when prospective renters are fully informed of an event. The possibility was raised that under incomplete information, the implicit impact may not exist even when the hedonic estimates are significant. This problem was addressed by Kask and Maani (1992) and Pope (2008a, 2008b); when assessing policy implications, one should use caution in interpreting results of a hedonic model that is estimated under incomplete information.

To explore hidden factors behind the hedonic estimates, such as the externality under complete information and the possibility that prospective renters are aware of each stigmatized property, three cases were considered with different assumptions. Under each assumption, the relationships were derived between estimates and the hidden factors, and possible implications were examined by using the estimated coefficients. Although the implications of hidden factors could vary among these cases, they all ensured that a negative externality existed within the building and block for incidents of homicide and suicide, respectively. Furthermore, a spatial externality outside the one-block area was observed for homicide, suicide, and death by fire 1 year after the incident, whereas that evidence became weaker as more time passed after the incident.

2.7. Tables and Figures

Table 2.1. Definitions of variables

Variable	Definition
Stigmatized property	
Discovery	1 = body found; 0 = otherwise
Fire	1 = death by fire; 0 = otherwise
Suicide	1 = suicide; 0 = otherwise
Homicide	1 = homicide; 0 = otherwise
EventYear	Year when a stigmatizing event happened
Rental housing unit	
Rent	Rental price per month (yen/month)
Distance	Distance from the closest stigmatized property (mile)
Building	1 = stigmatized property located in the same building; 0 = otherwise
Block	1 = stigmatized property located in the same block; 0 = otherwise
#Events (*0.2miles*)	Number of stigmatized properties within 0.2 miles
#Events (*0.3miles*)	Number of stigmatized properties within 0.3 miles
#Events (*0.5miles*)	Number of stigmatized properties within 0.5 miles
WalkTime	Time to the closest train station on foot (minute)
FloorLevel	Floor level
Stories	Total number of floor levels in a building
ft2	Floor space (square foot)
#Bedrooms	Number of bedrooms
BuiltYear	Year when an apartment building was completed
Building type	
Apartment1	1 = standard apartment; 0 = otherwise
Townhouse	1 = townhouse; 0 = otherwise
Terraced	1 = terraced house; 0 = otherwise
Apartment2	1 = luxury apartment; 0 = otherwise
House	1 = family home; 0 = otherwise
Dorm	1 = dormitory; 0 = otherwise
Building structure	
PC	1 = prestressed concrete; 0 = otherwise
RC	1 = reinforced concrete; 0 = otherwise
SRC	1 = steel-reinforced concrete; 0 = otherwise
Steel	1 = steel; 0 = otherwise
Wooden	1 = wooden; 0 = otherwise
Other	1 = none of the above; 0 = any one of the above

Table 2.2. Basic statistics

Variable	Minimum	Median	Maximum	Mean	S.D.	Sum
Stigmatized property						
Discovery	0	0	1	0.199	0.399	189
Fire	0	0	1	0.324	0.468	308
Suicide	0	0	1	0.203	0.403	193
Homicide	0	0	1	0.274	0.446	260
EventYear	1954	2008	2011	2005	8.92	—
Rental housing unit						
Rent	1.5	7.5	190	8.273	3.801	—
Distance	0	0.309	5.725	0.409	0.365	—
Building	0	0	1	0.001	0.038	198
Block	0	0	1	0.010	0.098	1,348
#Events (*0.2miles*)	0	0	13	0.391	0.759	—
#Events (*0.3miles*)	0	0	16	0.883	1.295	—
#Events (*0.5miles*)	0	2	33	2.381	2.810	—
WalkTime	0	7	125	8.308	5.359	—
FloorLevel	-8	2	58	2.678	2.303	—
Stories	1	3	101	4.296	3.591	—
ft2	33.368	268.667	5,334.804	329.258	168.322	—
#Bedrooms	1	1	8	1.323	0.602	—
BuiltYear	1950	1997	2012	1996.380	10.940	—
Building type						
Apartment1	0	0	1	0.428	0.495	58,785
Townhouse	0	0	1	0.000	0.010	13
Terraced	0	0	1	0.004	0.064	571
Apartment2	0	1	1	0.564	0.496	77,362
House	0	0	1	0.004	0.062	536
Dorm	0	0	1	0.000	0.003	1
Building structure						
PC	0	0	1	0.004	0.061	516
RC	0	0	1	0.367	0.482	50,331
SRC	0	0	1	0.056	0.230	7,713
Steel	0	0	1	0.013	0.112	1,738
Wooden	0	0	1	0.296	0.457	40,679
Other	0	0	1	0.264	0.441	36,291

Table 2.3. Estimation results of equations (2.7) and (2.8)

	[3-1]	[3-2]	[3-3]	[3-4]	[3-5]	[3-6]
		Equation (2.7)			Equation (2.8)	
Variable	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(*Distance* + 1) ×						
Discovery				0.0004	0.0018	0.0011
				(0.0016)	(0.0012)	(0.0009)
Fire				0.0029**	0.0031***	0.0016**
				(0.0014)	(0.0010)	(0.0008)
Suicide				0.0034**	0.0008	-0.0013
				(0.0016)	(0.0011)	(0.0008)
Homicide				0.0042***	0.0019*	0.0011
				(0.0015)	(0.0011)	(0.0008)
Building ×						
Discovery	-0.0245	-0.0221	-0.0267	-0.0237	-0.0217	-0.0260
	(0.0289)	(0.0278)	(0.0301)	(0.0288)	(0.0278)	(0.0300)
Fire	-0.0217	-0.0288**	-0.0342**	-0.0218	-0.0286**	-0.0342**
	(0.0147)	(0.0144)	(0.0142)	(0.0147)	(0.0144)	(0.0142)
Suicide	-0.0133	-0.0114	-0.0015	-0.0130	-0.0111	-0.0014
	(0.0273)	(0.0263)	(0.0256)	(0.0273)	(0.0263)	(0.0256)
Homicide	-0.0536***	-0.0562***	-0.0532***	-0.0538***	-0.0561***	-0.0532***
	(0.0142)	(0.0139)	(0.0141)	(0.0142)	(0.0139)	(0.0141)
Block ×						
Discovery	0.0046	0.0043	0.0006	0.0069	0.0160	0.0077
	(0.0090)	(0.0092)	(0.0089)	(0.0136)	(0.0119)	(0.0108)
Fire	0.0114**	0.0086*	0.0098*	0.0300***	0.0291***	0.0211***
	(0.0052)	(0.0051)	(0.0051)	(0.0105)	(0.0085)	(0.0073)
Suicide	-0.0398***	-0.0375***	-0.0389***	-0.0183	-0.0321***	-0.0480***
	(0.0090)	(0.0098)	(0.0097)	(0.0135)	(0.0120)	(0.0112)
Homicide	0.0152**	0.0169**	0.0156**	0.0421***	0.0293***	0.0228***
	(0.0068)	(0.0068)	(0.0068)	(0.0119)	(0.0099)	(0.0088)
ln(*EventAge*) ×						
Discovery	0.0138***	0.0003	0.0005	0.0115***	-0.0007	-0.0020
	(0.0037)	(0.0028)	(0.0023)	(0.0036)	(0.0027)	(0.0022)
Fire	-0.0027	-0.0061***	-0.0070***	-0.0013	-0.0067***	-0.0068***
	(0.0030)	(0.0022)	(0.0018)	(0.0029)	(0.0021)	(0.0017)
Suicide	0.0004	0.0022	0.0041***	0.0005	0.0029**	0.0047***
	(0.0022)	(0.0014)	(0.0011)	(0.0021)	(0.0014)	(0.0011)
Homicide	-0.0047*	-0.0013	-0.0043***	-0.0048*	-0.0013	-0.0039**
	(0.0026)	(0.0020)	(0.0016)	(0.0025)	(0.0019)	(0.0015)

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	[3-1]	[3-2]	[3-3]	[3-4]	[3-5]	[3-6]
		Equation (2.7)			Equation (2.8)	
Variable	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(#*Events*)	0.0235***	-0.0148	-0.0144*	-0.0127	-0.0127	0.0241***
	(0.0049)	(0.0166)	(0.0079)	(0.0166)	(0.0079)	(0.0049)
ln(#*Events*)^2	-0.0040**	0.0116	0.0099***	0.0114	0.0097***	-0.0040**
	(0.0017)	(0.0077)	(0.0033)	(0.0077)	(0.0033)	(0.0017)
ln(*WalkTime*)	0.0537***	0.0282***	0.0439***	0.0276***	0.0434***	0.0535***
	(0.0037)	(0.0067)	(0.0048)	(0.0067)	(0.0048)	(0.0037)
ln(*WalkTime*)^2	-0.0187***	-0.0127***	-0.0167***	-0.0125***	-0.0166***	-0.0186***
	(0.0010)	(0.0018)	(0.0012)	(0.0018)	(0.0012)	(0.0010)
ln(*ft2*)	-0.4004***	-0.4724***	-0.4183***	-0.4719***	-0.4182***	-0.4003***
	(0.0227)	(0.0345)	(0.0289)	(0.0345)	(0.0289)	(0.0227)
ln(*ft2*)^2	0.1492***	0.1622***	0.1533***	0.1621***	0.1533***	0.1492***
	(0.0034)	(0.0051)	(0.0043)	(0.0051)	(0.0043)	(0.0034)
ln(*Age*)	0.1469***	0.1414***	0.1493***	0.1414***	0.1493***	0.1470***
	(0.0021)	(0.0034)	(0.0026)	(0.0034)	(0.0026)	(0.0021)
ln(*Age*)^2	-0.0555***	-0.0539***	-0.0556***	-0.0539***	-0.0556***	-0.0556***
	(0.0005)	(0.0008)	(0.0006)	(0.0008)	(0.0006)	(0.0005)
ln(*FloorLevel*)	0.0240***	0.0249***	0.0256***	0.0249***	0.0256***	0.0240***
	(0.0017)	(0.0027)	(0.0020)	(0.0027)	(0.0020)	(0.0017)
ln(*FloorLevel*)^2	0.0052***	0.0052***	0.0045***	0.0052***	0.0045***	0.0052***
	(0.0008)	(0.0012)	(0.0010)	(0.0012)	(0.0010)	(0.0008)
ln(*Stories*)	0.0159***	-0.0219***	0.0036	-0.0215***	0.0036	0.0160***
	(0.0048)	(0.0072)	(0.0057)	(0.0072)	(0.0057)	(0.0048)
ln(*Stories*)^2	0.0043***	0.0156***	0.0078***	0.0155***	0.0078***	0.0043***
	(0.0014)	(0.0020)	(0.0016)	(0.0020)	(0.0016)	(0.0014)
ln(#*Bedrooms*)	0.0251***	0.0337***	0.0304***	0.0335***	0.0303***	0.0250***
	(0.0067)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0067)
ln(#*Bedrooms*)^2	-0.0367***	-0.0553***	-0.0471***	-0.0551***	-0.0470***	-0.0366***
	(0.0084)	(0.0101)	(0.0122)	(0.0101)	(0.0122)	(0.0084)
Observations	35,545	60,774	92,436	35,545	60,774	92,436
R-squared	0.909	0.904	0.902	0.909	0.904	0.903

Dependent variable is ln(Rent/ft2)i. ***, **, * indicate statistical significance at the 1, 5 and 10% levels using two-sided tests. Figures in parentheses are White's robust standard deviations. Coefficients of a constant and of dummy variables for building types, building structures, train stations and event types are not shown in the table. Age is the number of years passed since the building was completed (i.e. Age = Year of data – BuiltYear).

Table 2.4. Estimation results for equations (2.9) and (2.10)

	[4-1]	[4-2]	[4-3]	[4-4]	[4-5]	[4-6]
	Equation (2.9)			Equation (2.10)		
Variable	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(*Distance* + 1) ×						
Discovery				0.0111**	0.0086**	0.0066***
				(0.0051)	(0.0035)	(0.0025)
Discovery × ln(*EventAge*)				-0.0027	-0.0040*	-0.0010
				(0.0035)	(0.0024)	(0.0017)
Fire				0.0142***	0.0096***	0.0076***
				(0.0051)	(0.0035)	(0.0025)
Fire × ln(*EventAge*)				-0.0084***	-0.0038*	-0.0043***
				(0.0033)	(0.0022)	(0.0016)
Suicide				0.0149***	0.0079**	0.0047*
				(0.0052)	(0.0034)	(0.0024)
Suicide × ln(*EventAge*)				-0.0075***	-0.0057***	-0.0031***
				(0.0027)	(0.0017)	(0.0011)
Homicide				0.0151***	0.0084**	0.0070***
				(0.0051)	(0.0035)	(0.0025)
Homicide × ln(*EventAge*)				-0.0055*	-0.0031	-0.0040***
				(0.0031)	(0.0020)	(0.0014)
Building ×						
Discovery	0.0687	0.0569	0.0829	0.0699	0.0569	0.0812
	(0.0798)	(0.0774)	(0.0832)	(0.0805)	(0.0775)	(0.0833)
Discovery × ln(*EventAge*)	-0.0563	-0.0505	-0.0671	-0.0568	-0.0506	-0.0663
	(0.0472)	(0.0461)	(0.0503)	(0.0475)	(0.0461)	(0.0503)
Fire	0.0370	0.0025	-0.0142	0.0383	0.0034	-0.0137
	(0.0753)	(0.0721)	(0.0710)	(0.0754)	(0.0720)	(0.0710)
Fire × ln(*EventAge*)	-0.0374	-0.0200	-0.0129	-0.0380	-0.0204	-0.0132
	(0.0444)	(0.0430)	(0.0427)	(0.0445)	(0.0430)	(0.0426)
Suicide	0.0556	0.0627	0.0784	0.0542	0.0607	0.0765
	(0.0534)	(0.0522)	(0.0499)	(0.0533)	(0.0520)	(0.0498)
Suicide × ln(*EventAge*)	-0.0305	-0.0332	-0.0370*	-0.0295	-0.0320	-0.0362*
	(0.0225)	(0.0216)	(0.0210)	(0.0224)	(0.0214)	(0.0208)
Homicide	-0.2037***	-0.2097***	-0.1910**	-0.2028***	-0.2097***	-0.1917**
	(0.0735)	(0.0737)	(0.0763)	(0.0737)	(0.0737)	(0.0761)
Homicide × ln(*EventAge*)	0.0874**	0.0894**	0.0804*	0.0869**	0.0895**	0.0809*
	(0.0406)	(0.0410)	(0.0427)	(0.0407)	(0.0410)	(0.0426)
Block ×						
Discovery	-0.0645*	-0.0652*	-0.0644*	0.0266	-0.0076	-0.0199
	(0.0353)	(0.0358)	(0.0336)	(0.0478)	(0.0426)	(0.0376)
Discovery × ln(*EventAge*)	0.0448**	0.0456**	0.0428**	0.0151	0.0189	0.0371
	(0.0211)	(0.0215)	(0.0195)	(0.0304)	(0.0267)	(0.0229)
Fire	0.0023	0.0059	0.0071	0.0918**	0.0650*	0.0535*
	(0.0247)	(0.0243)	(0.0241)	(0.0406)	(0.0335)	(0.0295)
Fire × ln(*EventAge*)	0.0059	0.0019	0.0021	-0.0472*	-0.0201	-0.0238
	(0.0155)	(0.0152)	(0.0151)	(0.0260)	(0.0213)	(0.0188)
Suicide	-0.1182***	-0.1275***	-0.1309***	-0.0260	-0.0711**	-0.0883***
	(0.0253)	(0.0272)	(0.0268)	(0.0413)	(0.0354)	(0.0316)
Suicide × ln(*EventAge*)	0.0368***	0.0418***	0.0421***	-0.0099	0.0020	0.0169
	(0.0096)	(0.0102)	(0.0101)	(0.0194)	(0.0152)	(0.0129)
Homicide	0.0560**	0.0580**	0.0436	0.1482***	0.1155***	0.0888***
	(0.0264)	(0.0270)	(0.0270)	(0.0419)	(0.0357)	(0.0320)
Homicide × ln(*EventAge*)	-0.0231	-0.0235	-0.0159	-0.0562**	-0.0453**	-0.0419**
	(0.0144)	(0.0149)	(0.0149)	(0.0241)	(0.0201)	(0.0179)

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	[4-1]	[4-2]	[4-3]	[4-4]	[4-5]	[4-6]
		Equation (2.9)			Equation (2.10)	
Variable	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(*EventAge*) ×						
Discovery	0.0008	-0.0014	0.0003	0.0304	0.0258	0.0062
	(0.0019)	(0.0013)	(0.0011)	(0.0222)	(0.0161)	(0.0121)
Fire	-0.0022	-0.0019	-0.0020*	0.0520**	0.0193	0.0228**
	(0.0018)	(0.0013)	(0.0010)	(0.0209)	(0.0150)	(0.0114)
Suicide	0.0010	-0.0002	-0.0002	0.0475***	0.0406***	0.0262***
	(0.0013)	(0.0009)	(0.0007)	(0.0170)	(0.0115)	(0.0082)
Homicide	-0.0011	-0.0016	-0.0018**	0.0315	0.0205	0.0239**
	(0.0016)	(0.0011)	(0.0009)	(0.0195)	(0.0136)	(0.0100)
ln(#*Events*)	-0.0144	-0.0133*	0.0237***	-0.0135	-0.0114	0.0241***
	(0.0166)	(0.0079)	(0.0049)	(0.0166)	(0.0079)	(0.0049)
ln(#*Events*)^2	0.0114	0.0094***	-0.0040**	0.0119	0.0091***	-0.0040**
	(0.0077)	(0.0033)	(0.0017)	(0.0077)	(0.0033)	(0.0017)
ln(*WalkTime*)	0.0284***	0.0439***	0.0537***	0.0282***	0.0435***	0.0535***
	(0.0067)	(0.0048)	(0.0037)	(0.0067)	(0.0048)	(0.0037)
ln(*WalkTime*)^2	-0.0127***	-0.0167***	-0.0187***	-0.0127***	-0.0166***	-0.0187***
	(0.0018)	(0.0012)	(0.0010)	(0.0018)	(0.0012)	(0.0010)
ln(*ft2*)	-0.4731***	-0.4186***	-0.4007***	-0.4732***	-0.4184***	-0.4004***
	(0.0345)	(0.0289)	(0.0227)	(0.0345)	(0.0289)	(0.0227)
ln(*ft2*)^2	0.1623***	0.1534***	0.1492***	0.1623***	0.1533***	0.1492***
	(0.0051)	(0.0043)	(0.0034)	(0.0051)	(0.0043)	(0.0034)
ln(*Age*)	0.1415***	0.1494***	0.1469***	0.1417***	0.1494***	0.1470***
	(0.0034)	(0.0026)	(0.0021)	(0.0034)	(0.0026)	(0.0021)
ln(*Age*)^2	-0.0539***	-0.0556***	-0.0556***	-0.0539***	-0.0556***	-0.0556***
	(0.0008)	(0.0006)	(0.0005)	(0.0008)	(0.0006)	(0.0005)
ln(*FloorLevel*)	0.0248***	0.0255***	0.0240***	0.0248***	0.0255***	0.0239***
	(0.0027)	(0.0020)	(0.0017)	(0.0027)	(0.0020)	(0.0017)
ln(*FloorLevel*)^2	0.0052***	0.0045***	0.0052***	0.0052***	0.0045***	0.0052***
	(0.0012)	(0.0010)	(0.0008)	(0.0012)	(0.0010)	(0.0008)
ln(*Stories*)	-0.0221***	0.0034	0.0158***	-0.0216***	0.0036	0.0157***
	(0.0072)	(0.0057)	(0.0048)	(0.0072)	(0.0057)	(0.0048)
ln(*Stories*)^2	0.0157***	0.0079***	0.0044***	0.0156***	0.0078***	0.0044***
	(0.0020)	(0.0016)	(0.0014)	(0.0020)	(0.0016)	(0.0014)
ln(#*Bedrooms*)	0.0342***	0.0306***	0.0252***	0.0342***	0.0304***	0.0251***
	(0.0092)	(0.0092)	(0.0067)	(0.0092)	(0.0092)	(0.0067)
ln(#*Bedrooms*)^2	-0.0558***	-0.0473***	-0.0368***	-0.0556***	-0.0469***	-0.0366***
	(0.0101)	(0.0122)	(0.0084)	(0.0101)	(0.0122)	(0.0084)
Observations	35,545	60,774	92,436	35,545	60,774	92,436
R-squared	0.909	0.904	0.902	0.909	0.904	0.903

Dependent variable is ln(Rent/ft2)i. ***, **, * indicate statistical significance at the 1, 5 and 10% levels using two-sided tests. Figures in parentheses are White's robust standard deviations. Coefficients of a constant and of dummy variables for building types, building structures, train stations and event types are not shown in the table. Age is the number of years passed since the building was completed (i.e. Age = Year of data – BuiltYear).

Table 2.5. Coefficients and F-tests across event-types

Building

	1 year		5 years		10 years	
F-test (Ha)	P-value	Criteria	P-value	Criteria	P-value	Criteria
{D,F}	0.759		0.961		0.815	
{D,S}	0.874		0.480		0.364	
{D,H}	0.013 **	+	0.177		0.243	
{F,S}	0.841		0.365		0.424	
{F,H}	0.024 **	+	0.058 *		0.263	
{S,H}	0.005 ***	+	0.035 **	+	0.755	
t-test	Coefficient	Criteria	Coefficient	Criteria	Coefficient	Criteria
D	0.071		-0.021		-0.061	
F	0.037		-0.023		-0.049	
S	0.056		0.006		-0.015	
H	-0.202 ***	+	-0.063 ***	+	-0.003	

Block

	1 year		5 years		10 years	
F-test (Ha)	P-value	Criteria	P-value	Criteria	P-value	Criteria
{D,F}	0.282		0.675		0.503	
{D,S}	0.079 *		0.000 ***	+	0.001 ***	+
{D,H}	0.031 **		0.354		0.181	
{F,S}	0.001 ***	+	0.000 ***	+	0.001 ***	+
{F,H}	0.177		0.485		0.451	
{S,H}	0.000 ***	+	0.000 ***	+	0.004 ***	+
t-test	Coefficient	Criteria	Coefficient	Criteria	Coefficient	Criteria
D	-0.045		0.008		0.030 *	
F	0.001		0.012 **		0.016	
S	-0.122 ***	+	-0.061 ***	+	-0.034 ***	+
H	0.051 *		0.018 **		0.004	

ln(*Distance*+1)

	1 year		5 years		10 years	
F-test (Ha)	P-value	Criteria	P-value	Criteria	P-value	Criteria
{D,F}	0.010 ***	+	0.081 *		0.046 **	
{D,S}	0.002 ***	+	0.363		0.237	
{D,H}	0.001 ***	+	0.887		0.645	
{F,S}	0.493		0.540		0.581	
{F,H}	0.366		0.072 *		0.089 *	
{S,H}	0.871		0.373		0.380	
t-test	Coefficient	Criteria	Coefficient	Criteria	Coefficient	Criteria
D	0.0111 **	+	0.0067 **	+	0.0048	
F	0.0142 ***	+	0.0007		-0.0051	
S	0.0149 ***	+	0.0029		-0.0023	
H	0.0151 ***	+	0.0062 **	+	0.0024	

Table 2.6. Implications of estimation results under three cases

Case 1		1 year	5 years	10 years
Building	θ_A^k, τ^k	H>0	H>0	-
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0
Block	θ_A^k, τ^k	S>0	S>0	S>0
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0
ln(*Distance*+1)	θ_A^k, τ^k	(D,F,S,H)>0	(D,H)>0	-
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0

Case 2		1 year	5 years	10 years
Building	$\theta_A^k + \theta_B^k$	H>D=F=S=0	H>S=0, D=F=0	-
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H
Block	$\theta_A^k + \theta_B^k$	S>F=H=0, D=0	S>D=F=H=0	S>D=F=H=0
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H>0
ln(*Distance*+1)	$\theta_A^k + \theta_B^k$	F=S=H>D>0	D=H>0, F=S=0	-
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H

Case 3		1 year	5 years	10 years
Building	τ^k	H>D=F=S=0	H>D=F=S>0	-
	θ_A^k	D=F=S>H	D=F=S>H	-
	θ_B^k	H≧D=F=S	H≧D=F=S=0	-
Block	τ^k	S>D=F=S=0	S>D=F=H=0	S>D=F=H=0
	θ_A^k	D=F=H>S	D=F=H>S	D=F=H>S
	θ_B^k	S≧D=F=H	S≧D=F=H	S≧D=F=H
ln(*Distance*+1)	τ^k	F=S=H>D	-	-
	θ_A^k	D>F=S=H	-	-
	θ_B^k	F=S=H≧D	-	-

Figure 2.1. Number of stigmatizing events recorded on Jikobukken.com.

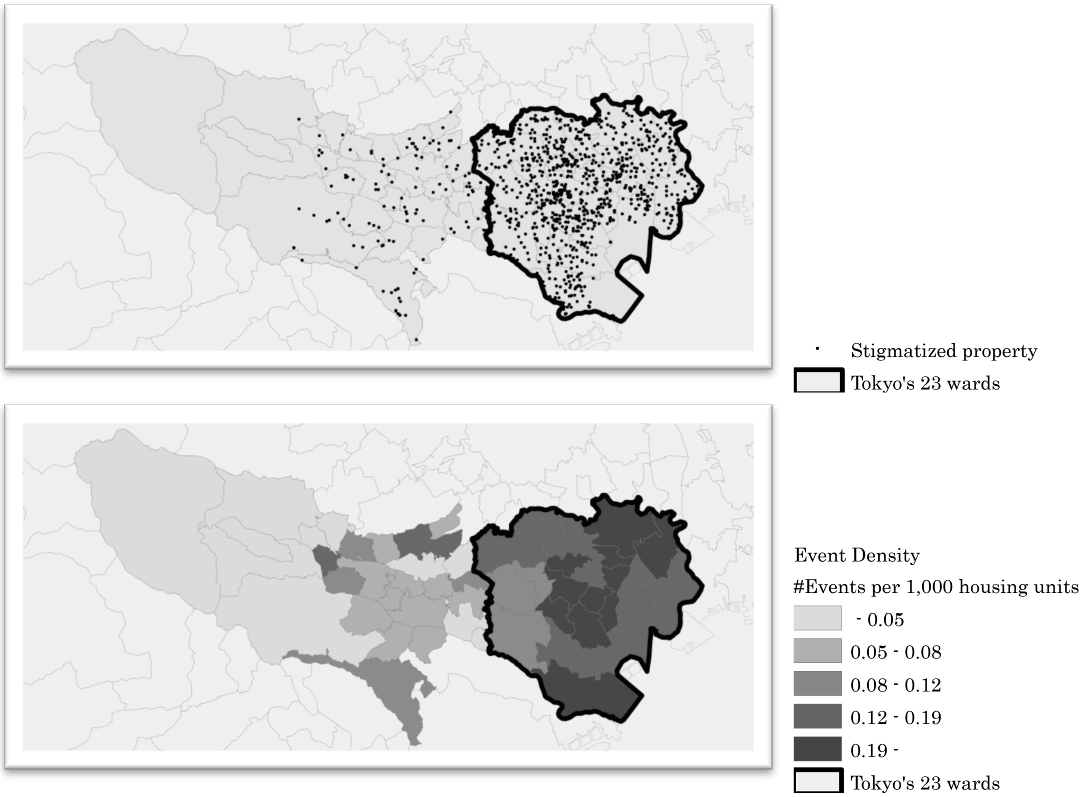


Figure 2.2. Event density by the type of event.

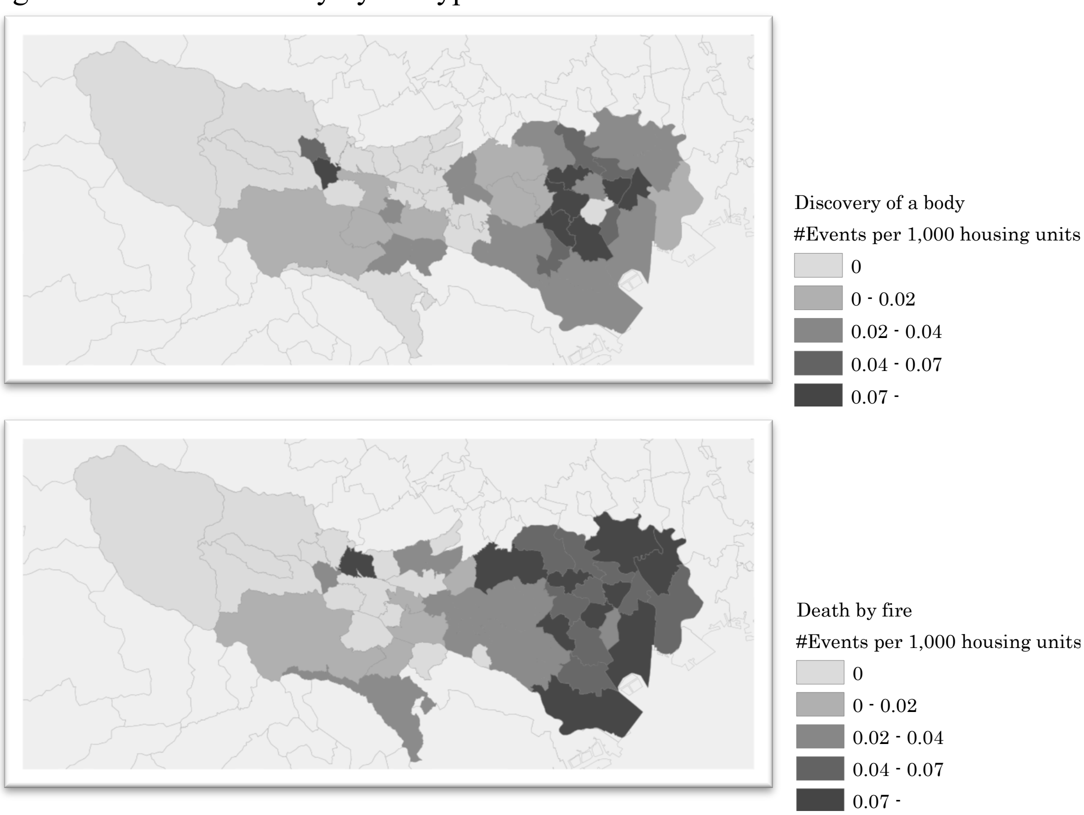
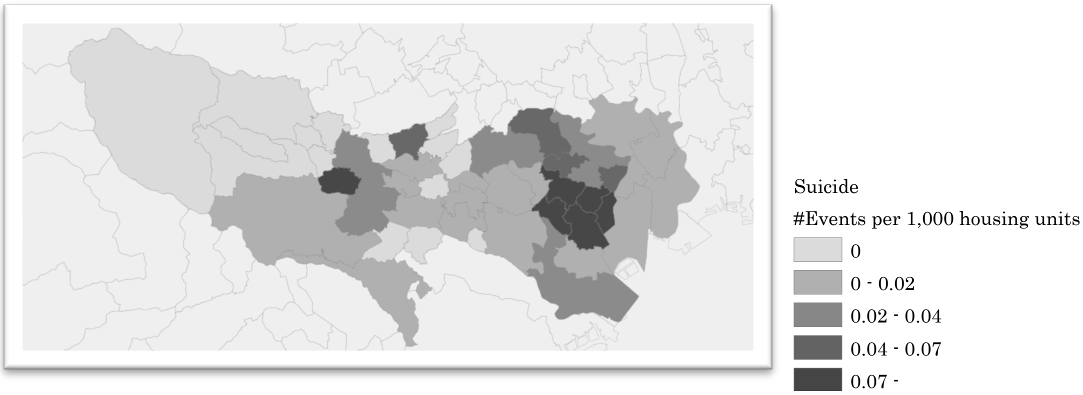


Figure 2.2. (cont.)



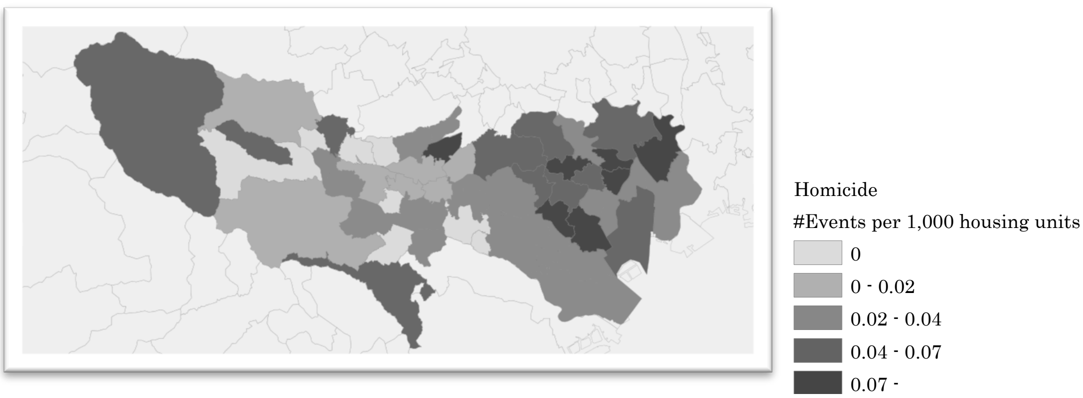


Figure 2.3: Hedonic price under incomplete information (from Pope; 2008b)

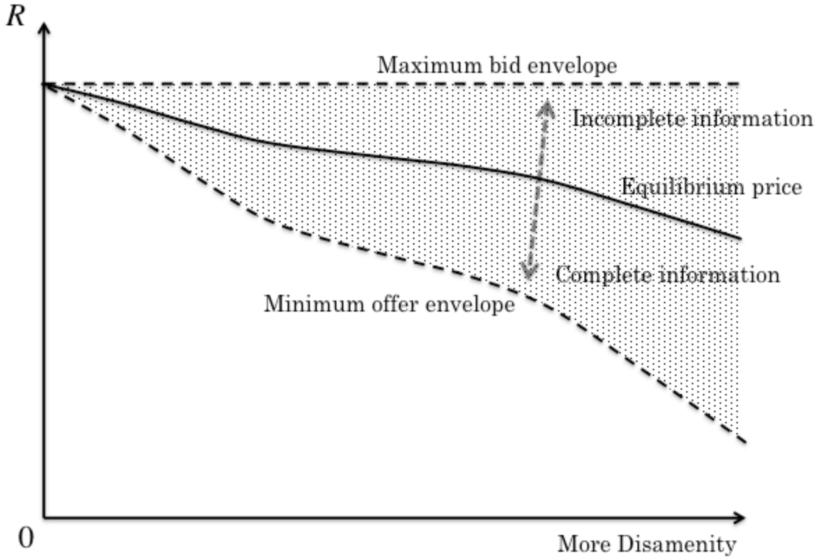


Figure 2.4

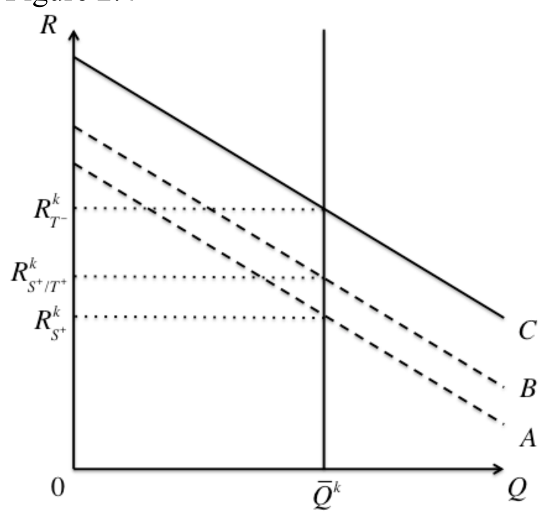
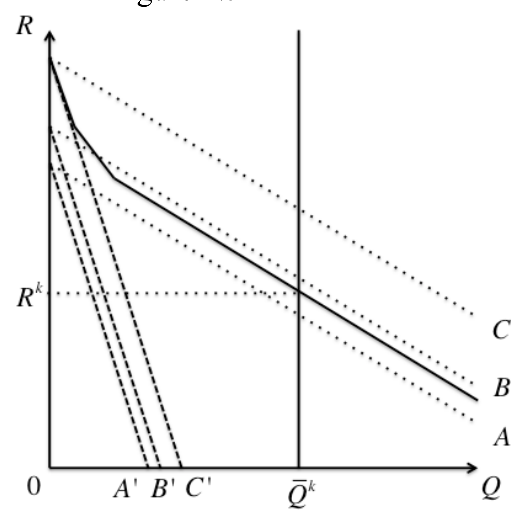


Figure 2.5



Chapter 3. Measuring the Spatial Effect of Multiple Sites

3.1. Introduction

Geographical relationships between a housing unit and the surrounding major sites, such as public transportation, commercial facilities, schools, and crime scenes, as well as the characteristics of those sites, are fundamental factors determining the value of housing. In this paper, an empirical model is developed to estimate the aggregate spatial effect of multiple sites that accounts for the following three general assumptions: (A1) the closer a site, the greater its impact may be; (A2) an impact may differ by the characteristics of a site; and (A3) the higher the ranking of proximity to a site, the greater the impact may be.

In previous literature studies, three types of proximity variables have predominantly been used for the examination of the externality of such multiple sites by using point-to-point data (accompanied by detailed addresses of housing and sites), namely, (i) the distance between a housing unit and its closest site,[32] (ii) the number of sites within a certain distance from a housing unit,[33] and (iii) an indicator of whether any site is located within a certain distance from a housing unit,[34] whereas none of the proximity variables satisfies all the general assumptions above (table 3.1). The use of each of these variables is justifiable under strict criteria, and failure to meet the criteria can lead to a biased estimate (table 3.2). For instance, using only the first type of proximity variable (i.e., the distance to the closest site) in the hedonic estimation assumes that the second closest site and the third closest site have no influence on the housing

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[32] Troy and Grove (2008), for example, compute the distance to the nearest park from each housing unit in Maryland and examine the impact of the crime rate at the park on neighboring housing values. Dorantes et al. (2011) and Gobbons and Machin (2005) both estimate the impact of the public transport infrastructure by comparing the coefficients of the distance to the closest stations before and after completion of the infrastructure. Ahlfeldt (2011) and Ahlfeldt and Wendland (2010) include minimum distances to various locations, such as the station, main road, school, water space, green space, and industrial area, to estimate the land price.

[33] Many studies on the impact of foreclosures on neighborhoods use this type of variable (Harding et al., 2009; Immergluck and Smith, 2006; Leonardo and Murdoch, 2009; Lin et al., 2009; Rogers and Winter, 2009; Schwartz et al., 2006; Shuetz et al., 2008). Instead of simply counting the sites, Srour et al. (2002) estimate the impact of social recreation areas, shopping centers, and workplaces by counting the number of retail employments and total employments and by measuring the area of park space, respectively.

[34] Linden and Rockoff (2008) use dummy variables indicating whether any sex offender is living within 0.1 mile and within 0.1 to 0.3 mile from a transactional housing unit to estimate its impact on the property value. Other papers using this type of variable include studies on the impact of wind power projects (Ben, 2010) and the impact of rail transit stations on housing values (Bowes and Ihlanfeldt, 2001; Forrest et al., 1995; Kahn, 2007).

value; this assumption is likely to result in an overestimation of the impact of the closest site.[35] One possible solution to address the effect of multiple sites is to regress a housing value on distances to the first closest site, the second closest site, the third closest site, and so forth. However, adding multiple distances in the hedonic model would lead to a serious multicollinearity problem, preventing the analyst from drawing reliable and meaningful interpretations of the spatial effect.[36] Another possible remedy is to coordinate the second type of proximity variables with the first type,[37] or to use a distance-weighted sum of sites within a certain area.[38] The main concern with these practices is the choice of an adequate buffer, which researchers typically determine in an arbitrary manner. Some literature studies attempt to avoid problems associated with multiple sites and spatial heterogeneity by restricting housing samples to those located very close to sites, rather than by implementing variables to account for multiple sites.[39]

The proposed proximity measure is based on another type of proximity measure, namely, an "accessibility measure," which has been developed in different fields of study, such as land use and transportation.[40] The accessibility measure is characterized as a sum of gravity-based functions, each of which is decreasing in distance and increasing in the attractiveness of a destination. Among the numerous existing studies, the ones that apply the accessibility measure to the hedonic approach are listed in table 3.3. It is interesting that most of the accessibility measures used in these studies are based on zone-to-zone measures rather than on

[35] This is because distances to the second and third closest sites, which may influence the housing value, are usually positively correlated with the distance to the closest site. Omitting these variables will lead to the upward bias of the effect of the closest site. Table 3.2 describes functional restrictions and potential biases caused by each proximity variable.

[36] In Appendix E, the results of our application show that variance inflation factors (VIFs) of distance variables exceed the value of ten when we include distances to the first three closest sites.

[37] Sadayuki (2013) examines the externality of stigmatized property on neighbor housing values by using the shortest distance to a stigmatized property for each housing unit in the estimation. As an explanatory variable, he includes a count of stigmatized properties within a certain range of each housing unit to control for the impact of the clustering of stigmatized properties.

[38] Campbell et al. (2011) study the impact of foreclosures, but make variables by combining the first two types. One variable is a count of foreclosures within 0.25 mile from each transactional housing unit, whereas the other variable is a distance-weighted sum of foreclosures within 0.01 mile.

[39] Pope (2008c) excludes housing units that have more than one sex offender living within 0.15 mile. McMillen and McDonald (2004) estimate the impact of the infrastructure of the Midway rapid transit line in Cook County, Illinois, by excluding housing units that are located farther than 1.5 miles from the Midway line or closer to other kinds of lines.

[40] To name a few, Hansen (1959), Song (1996), Ottensmann and Lindsey (2008), Iacono et al. (2010), and Salze et al. (2011).

point-to-point measures; i.e., the distances used in these accessibility measures are computed between zones (such as zip code areas, transportation analysis zones, and voting precincts), rather than between housing units and sites. This is done because the major purpose of these studies is to assess the accessibility from one city to employment opportunities in other cities by counting the number of employment or job opportunities in each area, thereby addressing the significance of a polycentric urban structure in determining the housing value. Appendix D provides farther discussion on the traditional accessibility measures versus the hedonic approach in the previous literature studies.

In comparison with these studies, the current focus is more of a local examination in which the spatial effect of such multiple sites such as public transportation, parks, supermarkets, foreclosures, and crime scenes are not likely to affect anyone beyond the neighborhood. The accessibility measure is superior to the other three types of proximity measures in the sense that it provides flexibility in the functional form adopted. However, it still fails to take into account the third assumption (A3), which would result in a biased estimate (see tables 3.1 and 3.2). In the proposed proximity measure, several modifications are made to the traditional accessibility measure to fit in the context of a point-to-point spatial analysis and to account for the third assumption (A3). In addition, the estimation procedure provide insights into some interesting questions in the context of a point-to-point spatial analysis, such as "How many neighbor sites affect the housing value?" and "To what extent does each site have an influence on the housing value?"

In the following section, two proximity measures that are equivalent to the traditional accessibility measures are presented, and then the preferred measures are revealed reflecting some minor modifications to the former models. In Section 3, an application is illustrated of the relationship between the housing rental value and the clustering of train and subway stations in Tokyo, Japan. Under a correct model, addressing a greater number of neighbor stations should be associated with a better estimation result. However, it is surprising to observe in the application that the traditional accessibility measure compromises the estimation result when a larger number of neighbor stations are included in the model. This result is due to its incorrect functional specification of the spatial effect by failing to account for the third assumption (A3). The proposed models solve this issue, and the estimation result improves with the number of stations considered in the model. Although almost all studies of the housing market in Tokyo consider only the distance to the nearest station in the hedonic model,[41] the present results suggest that at least the first three closest stations need to be taken into account to obtain a better estimate of the housing rent in Tokyo, whereas including more than the five closest stations in the model does not improve the prediction. Some additional examinations with generalized proximity measures are discussed in Appendix E. Finally, Section 4 offers conclusions from the study.

3.2. Estimation proposal

Traditional accessibility measure

Before introducing our proposed models, a traditional accessibility measure adjusted to fit in the context of our research is described. The main difference from the measures used in previous studies (described in Appendix D and table 3.3) is that the traditional accessibility measure in this section is constructed within the framework of a point-to-point spatial analysis. The subscript i is used to refer to the i^{th} housing unit and $s_{i(j)}$ to indicate the j^{th} closest site from housing i. Then, the traditional accessibility measure is described as follows:

$$G\left(\left\{d_{i(j)}, q_{i(j)}, k_{i(j)}\right\}_{j=1}^{J}\right) = \sum_{j=1}^{J} f\left(d_{i(j)}, q_{i(j)}, k_{i(j)}\right) + c_{(j)}. \tag{3.1}$$

Here, $G(.)$ is a gravity-base function; $d_{i(j)}$ is the distance from housing i to $s_{i(j)}$; $q_{i(j)}$ is a value representing quantitative characteristics of $s_{i(j)}$; $k_{i(j)}$ is a type of qualitative characteristics of $s_{i(j)}$; J is the number of the closest sites considered in the model; $f(.)$ specifies the functional form of the spatial effect of each site; and $c_{(j)}$ is a constant term for the j^{th} closest site.

Besides the difference in point-to-point and zone-to-zone measures, note two other major distinctions between the traditional accessibility measures in other literature studies and in this section. First, two kinds of characteristics of the sites are considered in the model. One type is quantitative characteristics, represented by $q_{i(j)}$, and the other is qualitative characteristics, $k_{i(j)}$, which is addressed by introducing an indicator, $D_{i(j)}^{k}$, to differentiate parameters among

[41] To name a few, Diewert and Shimizu (2016), Gao and Asami (2001), Nakagawa et al. (2007), Shimizu and Nishimura (2007), Shimizu et al. (2010) and Yamagata et al. (2016).

different types of sites. Here, $D^k_{(j)}$ takes a value of one if the qualitative characteristics of $s_{i(j)}$ are of type $k \in \{1, \dots K\}$ and takes a value of zero otherwise.[42] The following function is based on the most commonly used exponential-type accessibility measure;

$$f(.) = D^k_{i(j)} \tau^k q_{i(j)} e^{\alpha^k d_{i(j)}}, \tag{3.2}$$

in which τ^k and α^k are parameters. When there are *K* types of qualitative characteristics of sites, we have 2*K* parameters to be estimated in the measure. When only a single qualitative characteristic exists, $f(.)$ takes the following functional form: $f(.) = \tau q_{i(j)} e^{\alpha d_{i(j)}}$, where τ and α are the only two parameters in the accessibility measure to be estimated.[43] Based on equation (3.2), the spatial effect of the j^{th} closest site converges to a constant, $c_{(j)}$, as the distance increases. One can also construct an alternative formula that allows a different limit for each type, such as $f(.) = D^k_{i(j)} \left(\tau^k q_{i(j)} e^{\alpha^k d_{i(j)}} + \omega^k \right)$. However, when the true specification of the spatial effect is close to linear one with respect to distance, absolute values of α^k and τ^k as well as their standard errors become so large that the estimation fails to identify parameters.[44] Accordingly, in addition to equation (3.2), an alternative linear-type specification for $f(.)$ is examined as follows:

$$f(.) = D^k_{i(j)} (\tau^k q_{i(j)} + \alpha^k d_{i(j)} + \omega^k). \tag{3.3}$$

This formula assumes that the effects associated with the distance and the qualitative characteristics are independent. One advantage of this formula is that even when τ^k is zero, it still yields an estimate of α^k, whereas the proximity measure of equation (3.2) cannot.

The other distinction is that the traditional accessibility measure specified in this section is a sum of $f(.)$ for the first J closest sites, whereas the measure in previous literature studies (as described in Appendix D and table 3.3) is the sum of all destinations in the study area. Recall

[42] For instance, in the case of foreclosures (Xian and Hewings, 2016), the quantitative characteristic can be the time that has passed since the evacuation of the previous owner, and the qualitative characteristic can be whether the foreclosing property receives the Neighborhood Stabilization Program (NSP) grant. In the case of crime scenes, the quantitative characteristic can be the time that has passed since the incident, and the qualitative characteristics can be the types of incidents, such as homicides, robberies, and assaults.

[43] This is equivalent to equation (D1) in Appendix D.

[44] In our application, although the results are not shown in this paper, the author estimates hedonic models using several alternative specifications of the proximity measure including the one above, and find that sites with some qualitative characteristics have the linear relationship between the distance and the rent.

that the main objective of the previous literature was to examine the polycentric structure of labor markets, which requires a wide range in the study area to construct the accessibility measure because individuals may commute far.[45] In contrast, the spatial influence of foreclosures, crime scenes, and the access to public transportation is likely to be limited to a local area. In such point-to-point examinations, using all sites within an entire study area to construct a proximity measure does not seem rational. Instead, in this paper, the traditional accessibility measure is estimated using a different number of J and observe how adding the number of closest sites to the model improves the estimation.

Proposed proximity measure

The proposed proximity measure is described as follows:

$$G\left(\left\{j, d_{i(j)}, q_{i(j)}, k_{i(j)}\right\}_{j=1}^{J}\right) = \sum_{j=1}^{J} g(j,k) f\left(d_{i(j)}, q_{i(j)}, k_{i(j)}\right) + c_{(j)}. \tag{3.4}$$

A new term, $g(j,k)$, is introduced into the traditional accessibility measure in equation (3.1). This new term takes into account the third assumption (A3), such that $f(.)$ can be weighted differently depending on the proximity order and qualitative characteristics of a site. One rational specification is $g(j,k) = j^{\theta^k}$, where the parameter, θ^k, takes a negative value if the site with a higher order proximity is more important than the site of the same type with a lower order proximity. If all sites are equally important, θ^k takes a value of one, which reduces to equation (3.1). When there exists such a discounting factor with respect to the proximity order, the traditional accessibility measure (which does not take into account the third assumption) in the hedonic model is likely to overestimate the impact of the higher-order-proximity sites and underestimate the impact of the lower-order-proximity sites (table 3.3). A more general specification is $g(j,k) = \theta_{(j)}^{k}$, where the parameter differs by its proximity order and qualitative characteristics. Under this specification, the number of parameters increases by the number of qualitative characteristics, k, when J increases by one. There are two concerns of using this general specification. One is the multicollinearity problem because $f(.)$ is likely to

[45] According to the 2011 American Community Survey, among U.S. workers who did not work at home, 8.1 percent had commutes of 60 minutes or longer and 35.7% had commutes of 30 minutes or longer in 2011. Census Bureau. In Tokyo, Japan, 24.2% had commutes of 60 minutes or longer and 69.8% had commutes of 30 minutes or longer in 2013, according to the 2013 Housing and Land Survey conducted by the Ministry of Internal Affairs and Communications.

be highly correlated among different js, in which case $\theta_{(j)}^{k}$ may not give reliable interpretations. The other is the identification problem in which $\theta_{(j)}^{k}$ cannot be estimated if both $\theta_{(j)}^{k}$ and parameters in $f(.)$ are zero.

In the following application, we examine the relationship between housing rent and access to clustering stations and compare the results of the traditional accessibility measure with the proposed proximity measure. The functional specifications of the measures are based on equations (3.4), (3.5), and $g(j,k) = j^{\theta^k}$, whereas other results with additional specifications (including $g(j,k) = \theta_{(j)}^{k}$) are discussed in Appendix E.

3.3. Application

In this section, we examine the relationship between the housing rent and the surrounding train and subway stations by using cross-sectional data from Tokyo's 23 wards. First the data are presented, then the empirical models and finally the estimation results.

Data

Data on rental housing in Tokyo's 23 wards were collected from November 2011 to July 2012 from the website of a rental real estate agency, Door Chintai.[46] There are 14,404 housing sample units located in 8,955 rental apartment buildings after removing samples with missing values as well as outlying observations of rental prices above the 99th percentile and below the first percentile. The data include rental prices and housing characteristics such as address, floor area, number of bedrooms, floor levels, number of stories in a building, age of the building, amenities (gas, stove, and security systems), number of retail stores within 1 mile, and building type and structure.[47] Definitions of and basic statistics for the variables are described in tables 4 and 5, respectively. The average rent in Tokyo's 23 wards in the samples is about 89,600 yen per month, which is $896 per month based on an exchange rate of $1 = 100 yen. Most of the samples are apartment units and a few are family houses. The average number of floors is 2.96, and 26% of the samples are located on the first floor. The average floor area is 30.73 square meters (330.77 square feet), and the average age of the building is 16.74 years.

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[46] http://chintai.door.ac/.

[47] The geocoding system and the data on retail stores were provided by the Center for Spatial Information Science, The University of Tokyo.

We obtained geocodes for the existing train and subway stations as of October 2012 from the website EkiData.jp.[48] Figure 3.1 shows the train and subway stations around Tokyo's 23 wards. The data also include the names of the train and subway lines leading to each station. The number of lines leading to each station is used as a measure of the quantitative characteristics, $q_{i(j)}$. There are 490 stations in Tokyo's 23 wards, an additional 137 stations surrounding Tokyo's 23 wards are included in the analysis. Of the total 627 stations, 457 stations have one line, 105 stations have two lines, 41 stations have three lines, and 27 stations have four or more lines.

Using these data sets, Euclidian distances between all combinations of housing and stations were computed. Based on the computed distances, the first nine closest stations from each housing sample *i*, i.e., $s_{i(1)}, \ldots, s_{i(9)}$were computed. For the qualitative characteristics, k, the first nine closest stations from each housing sample were categorized into two groups, $k \in \{0,1\}$. One is a set of stations that have at least one line that does not lead to any stations closer to house i, i.e., k = 1. In other words, these stations are the closest stations to reach to certain line(s) from housing *i*. An indicator, $D^1_{i(j)}$, named "new-line dummy," has been constructed; it takes a value of one for such a station with a new line(s) and takes a value of zero otherwise. By construction, a new-line dummy for the closest station, $D^1_{i(1)}$, always takes a value of one. When a new-line dummy takes a value of zero, that indicates that all lines leading to the station also lead to closer stations from house *i*; in other words, this station is redundant in the sense that people living in house *i* can go to closer stations to take any lines leading to this station. Figure 3.2 is a visual illustration of how the values of the quantitative characteristics, $q_{i(j)}$, and the qualitative characteristics, $k_{i(j)}$, are assigned. Basic statistics on distances, numbers of lines, and new-line dummies are shown in table 3.6. The average distance to the closest station is 0.56 miles, and the average distances increase to 0.93 and 1.20 miles for the second and third closest stations. The average number of lines leading to a station ranges from 1.38 to 1.49. About half of the second closest stations have a new line that does not lead to the closest station, whereas the proportion of stations with a new line declines as the proximity order becomes lower.

Estimation models

[48] http://www.ekidata.jp/.

We estimate the hedonic rental price function as follows:

(7) $Rent_i = \sum_{j=1}^{J} G\left(\left\{j, d_{i(j)}, q_{i(j)}, D_{i(j)}^1, D_{i(j)}^0\right\}_{j=1}^{J}\right) + \mathbf{X}_i\boldsymbol{\beta} + e_i$,

where $Rent_i$ is the monthly rent of housing i; $G(.)$ is a proximity measure; $d_{i(j)}$ is the distance from housing i to $s_{i(j)}$; $q_{i(j)}$ is the number of lines leading to $s_{i(j)}$; J is the number of closest stations considered in the model; $\mathbf{X}_i$ is a variable for neighborhood and housing characteristics; and e_i is an error term. $D_{(j)}^1$ = 1 if $s_{i(j)}$ has a line that does not lead to any of the closer stations, $s_{i(1)}, \ldots, s_{i(j-1)}$, and $D_{(j)}^1$ = 0 otherwise. $D_{i(j)}^0$ = 1 if and only if $D_{(j)}^1$ = 0, i.e. all lines at $s_{i(j)}$ lead to either one of the closer stations, $s_{i(1)}, \ldots, s_{i(j-1)}$, and $D_{(j)}^0$ = 0 otherwise. Four types of proximity measures are examined:

Model A0 is based on the exponential-type traditional accessibility measure:

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^1 \tau^1 q_{i(j)} e^{\alpha^1 d_{i(j)}} + D_{i(j)}^0 \tau^0 q_{i(j)} e^{\alpha^0 d_{i(j)}} + c_{(j)}.$$

Model B0 is a linearized version of Model A0:

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^1\left(\tau^1 q_{i(j)} + \alpha^1 d_{i(j)}\right) + D_{i(j)}^0\left(\tau^0 q_{i(j)} + \alpha^0 d_{i(j)}\right) + D_{i(j)}^0 \omega^0 + c_{(j)}$$

$$= \tau^1 \sum_j D_{i(j)}^1 q_{i(j)} + \alpha^1 \sum_j D_{i(j)}^1 d_{i(j)} + \tau^0 \sum_j D_{i(j)}^0 q_{i(j)} + \alpha^0 \sum_j D_{i(j)}^0 d_{i(j)} + \omega^0 \sum_j D_{i(j)}^0.$$

Model A1 is the proposed proximity measure with weighting terms added to Model A0:

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^1 j^{\theta^1} \tau^1 q_{i(j)} e^{\alpha^1 d_{i(j)}} + D_{i(j)}^0 (j-1)^{\theta^0} \tau^0 q_{i(j)} e^{\alpha^0 d_{i(j)}} + c_{(j)}.$$

And Model B1 is the proposed proximity measure with weighting terms added to Model B0:

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^1 j^{\theta^1}\left(\tau^1 q_{i(j)} + \alpha^1 d_{i(j)}\right) + D_{i(j)}^0 (j-1)^{\theta^0}\left(\tau^0 q_{i(j)} + \alpha^0 d_{i(j)}\right) + D_{i(j)}^0 (j-1)^{\theta^2} \omega^0 + c_{(j)}$$

Model A0 is the traditional accessibility measure based on equation (3.2). Parameters differ between stations with and without a new line, namely, $D_{i(j)}^1$ = 1 and $D_{i(j)}^0$ = 1. Model B0 is a linearized version of Model A0, in an attempt to estimate the effects of quantitative characteristics and distance separately. Since Model B0 can be expressed as a linear function, OLS is used to estimate the hedonic function, whereas maximum likelihood method is employed for the hedonic functions using the other three measures. Model A0 has four parameters, τ^1,

α^1, τ^0, and α^0, and Model B0 has five parameters, τ^1, α^1, τ^0, α^0, and ω^0. When J = 1, there are only two parameters, τ^1 and α^1, to be estimated in both models because, for all the closest stations, $D^1_{i(1)}$ = 1 for all i.

Model A1 adds the weighting terms j^{θ^1} and $(j-1)^{\theta^0}$ to Model A0. If the spatial effect of a station diminishes with the proximity order ranking, these weighting parameters, θ^1 and θ^0, will be negative. To gain a better understanding of the weighting parameters, consider a case in which the closest station is located one mile away from house i. Suppose that a new station on a different line will be constructed just half a mile away from house i such that this new station will be the closest one and the former station will become the second closest in the near future. Will the impact of the former station on house i stay the same even after the new station is constructed? If the answer is yes, it implies that θ^1 = 0. If the impact of the former station is reduced because of the presence of the new station, then θ^1 < 0. The traditional accessibility measure can be regarded as a special case of Model A1, in which $\theta^1 = 0$ and $\theta^0 = 0$. When J = 1, there are only two parameters to be estimated, τ^1 and α^1, and the result will be the same as the result in Model A0. When J = 2, it is possible to estimate five parameters, τ^1, α^1, τ^0, α^0, and θ^1. When J = 3 or more, the model also estimates θ^0 in addition to the five parameters above because $D^0_{i(j)}$ varies from j = 2. This is why $(j-1)$ is used as the base of $g(j, k=0)$, so that τ^0 and α^0 indicate the effects of the second closest station without a line.[49] In contrast, τ^1 and α^1 indicate the effects of the closest station because we have j as the base of $g(j, k=1)$.

Model B1 is an extension of Model B0 with the weighting parameters θ^1, θ^0, and θ^2. Here, ω^0 indicates the rental difference between two housing units located at the second closest stations with and without a new line, k = 1 and k = 0, evaluated at $d_{i(2)} = 0$ and $q_{i(2)} = 0$. None of the second closest stations have such characteristics; thus, the rental difference will be evaluated at the mean value of $d_{i(2)}$ and at $q_{i(2)} = 1$ in the application. The model with J = 1 estimates two parameters, the model with J = 2 estimates six parameters, and models with greater numbers of stations estimate eight parameters.

[49] One can construct $g(j, k=0) = j^{\theta^0}$ instead; however, it would hinder us from gaining a direct interpretation of the parameter, and the estimates of θ^0 and τ^0 would lose stability across different J.

Estimation results

Model A0: Table 3.7 shows the maximum likelihood estimates of hedonic functions with the traditional exponential-type accessibility measure, Model A0. Each column shows the results using a different number of stations in the accessibility measure (i.e., J = 1, 2, 3, 5, and 9). The table shows the results of estimated parameters in the accessibility measures as well as coefficients of some control variables in **X**. Numbers in parentheses are cluster-robust standard errors, assuming that the residuals can be correlated within the same apartment buildings and independent across the buildings. In addition, the log likelihood, the corrected Akaike information criteria (AICc), and the Bayesian information criteria (BIC) are shown at the bottom of the table.

First, examine the parameters of the accessibility measure. Overall, τ^1 and α^1 show the expected signs and are statistically significant, implying that a station with a new line has a positive effect on the neighboring housing rent; i.e., the housing rent is higher near a station with more lines and is lower for housing that is located farther from the station. In contrast, τ^0 and α^0 are not significantly different from zero. This means that stations without a new line have no influence on the surrounding housing rent.

If the model specification is accurate, using more information on surrounding stations in the hedonic model should yield a better prediction on the housing rent. However, the log likelihood, AICc, and BIC indicate that adding more stations in the model (i.e., a greater J) diminishes the estimation result, and, therefore, one might suspect model misspecification. Another sign of the possibility of the misspecification can be seen in the unstable parameters across Js. τ^1 and α^1 change from 0.39 to 0.26 and from -1.52 to -2.24, respectively, as J increases from 1 to 9. This implies that marginal effects of distance and the number of lines vary with the proximity order of a station.

Model B0: Table 3.8 shows OLS estimates of parameters in Model B0.[50] The positive signs of τ^1 and τ^0 imply that the housing rent is higher if the surrounding stations have a greater number of lines. The negative sign of α^1 means that the housing rent increases for housing that is located closer to a station with a new line. On the other hand, α^0 is not significantly

[50] Hereafter, only the estimates of the parameters in the proximity measure are shown and coefficients of the control variables, ***X***, are omitted from the result tables.

different from zero, meaning that the distance to a neighbor station without a new line has no effect on the housing rent. Unlike the previous model, Model B0 estimates the effects of the number of lines and the distance separately. It reveals in this model that the number of lines at a station without a new line has a positive effect on the nearby housing rent, which is not shown in Model A0 where the marginal effects of distance and number of lines are assumed to be positively correlated by construction of the model.

Similar to the results in Model A0, the estimation result deteriorates as J increases, as can be seen in the R^2, log likelihood, AICc, and BIC. In addition, the parameters are not stable with different J, implying that the marginal effects differ by the proximity order of a station. In particular, magnitudes of the parameters become smaller as J increases, implying that the marginal effects are smaller for the stations with lower proximity orders. These issues arise as a result of the failure to account for assumption (A3), as can be confirmed in the following results of the proposed models.

Model A1: The first alternative model, Model A1, has a proximity measure in which a minor change in the traditional accessibility measure was made by adding weighting parameters, such that the assumption (A3) is taken into account. The estimation results are shown in table 3.9.

Note that the result in column [9-1] of table 3.9 is identical to the result in column [7-1] of table 3.7 for Model A0 because the functional forms of both models are the same when $J = 1$. When $J = 2$, the results of the two models may differ because of a difference in the relative importance of the first and second closest stations. The traditional accessibility measure assumes that the first and second closest stations are equally important to residents, i.e., $\theta^1 = 0$. According to [9-2], θ^1 is -2.27 and the sign is statistically significant, implying that people perceive the first closest station as being more important than the second closest station. In [9-3] to [9-5], θ^1 remains negative, whereas θ^0 is not statistically different from zero.

In contrast to the results for Model A0, adding a greater number of neighboring stations in Model A1 improves the estimation result. According to the AICc and BIC, the estimation improves as J increases to 5. In addition, α^1 becomes relatively stable in Model A1 compared with Model A0. Another distinction from the result for Model A0 is that some of α^0's turn out to be significant. Since τ^0 is negative, the negative α^0 means that the rent increases for housing located farther from a station without a line. However, recall that the exponential-type model such as Model A0 and Model A1 impose a positive correlation between marginal effects of the distance and the number of lines by construction. If this assumption is not true, as suggested in the result of the previous linear-type model, Model A1 fails to provide correct interpretations about the spatial effect. Unstable magnitudes of τ^0 and α^0 and their large standard errors are also the signs of the misspecification of the spatial model.

Figure 3.3 illustrates the housing rent versus the distance to a station, based on the result in [9-4]. Here, the number of lines leading to a station is fixed at one. Note that the levels of lines on the *y*-axis are not comparable across different proximity orders because $c_{(j)}$ is absorbed by a constant in the hedonic model and thus cannot be identified. When the distance to the closest station increases from 0.2 mile (10th percentile) to 1.0 mile (90th percentile), the monthly rent declines by about 2,200 yen ($22, with $1 = 100 yen) on average. In addition, when the distance to the second station with a new line increases from 0.5 mile (10th percentile) to 1.5 miles (90th percentile), the rent declines by about 500 yen ($5, with $1 = 100 yen). In contrast, the housing rent increases for housing is located farther from the second closest station without a new line.

Model B1: The estimation results for the second proposed model, Model B1, are described in table 3.10. Unlike the results for Model B0, the parameters become stable regardless of the choice of *J*. In addition, according to the AICc and BIC, the estimation result improves as a greater number of stations are considered in the model. As mentioned, adding more stations in the traditional accessibility measure worsens the estimation; this finding calls into question the credibility of using the traditional accessibility measure in research. However, the two proposed models solve this problem by introducing weighting terms that assess different weights for the effects of stations by their proximity orders. Between the two proposed models, the performance of Model B1 is superior to that of Model A1, based on the information criteria (figure 3.5). Both criteria decline until *J* reaches 5. Therefore, the results imply that the first five stations closest to each housing unit need to be considered to obtain a better prediction of the housing rent in Tokyo.

Now the focus turns to the result in [10-4].[51] Regarding a station with a new line, τ^1 is 0.19; the rent appreciates by 1,900 yen ($19) when the number of lines at the closest station increases

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[51] [10-4] is selected among [10-1] to [10-5] based on the AICc and BIC.

by one. α^1 is −0.57: the rent decreases by 5,700 yen ($57) as the distance to the closest station increases by 1.0 mile. θ^1 is negative: the marginal effects of the distance to and of the number of lines at a station with a new line diminish as its proximity order becomes lower. The marginal effects of these two variables are, respectively, 300 yen ($3) and 1,000 yen ($10) for the second closest station with a new line.

Regarding a station without a new line, α^0 and τ^0 are positive[52] but not statistically different from zero; the distance to and the number of lines at a station without a new line have no influence on the rent. This result implies that the number of lines at a station is not important to residents as long as they have access to these lines at closer stations. θ^0 shows a negative sign but it is not statistically significant. Finally, ω^0 is −0.40, i.e., the hypothetical rent of a housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$, and $D^1_{i(2)} = 1$ is higher than the hypothetical rent of housing with $d_{i(2)} = 0$, $q_{i(2)} = 0$, and $D^1_{i(2)} = 1$ by 4,000 yen ($40). The rental difference, evaluated at the average distance to the second closest station (0.93 mile) and $q_{i(2)} = 1$, is about 1,100 yen ($11). Considering a closer distance, for example, 0.50 mile (about the 10th percentile of the distance to the second closest station), the rental difference will be about 2,500 yen ($25).

Further estimations (Appendix E)

Alternative models are examined with some generalized specifications of the proposed proximity measures, Model A1 and Model B1. Two types of generalizations are tested for each of the two proposed models. In the first type, $g(j,k) = \theta^k_{(j)}$ such that discounting weights are free from the functional form, which is restricted to $g(j,k) = j^{\theta^k}$ in Model A1 and Model B1. In the second type, we allow all parameters to vary by proximity order and by their qualitative characteristics, i.e., $\tau^k_{(j)}$, $\alpha^k_{(j)}$, and $\omega^k_{(j)}$.

The estimation results and a detailed discussion are provided in Appendix E; the results can be summarized as follows. First, the generalizations of Model A1 lead to an identification

[52] One possible explanation of the positive is α^0 that the distance to the second closest station without a new line is likely positively correlated with the distance to a railway leading to the first two closest stations. A railway can be a disamenity to nearby housing because of the noise it generates (Andersson et al., 2010; Mrons et al., 2003; Diao et al., 2015; Poon, 1975). In future research, taking into account the distance to railways may provide further insights into our findings.

problem when $J = 4$ and higher, preventing the maximum likelihood estimation from identifying the parameters. This result is attributed to the fact that stations without a new line have too little effect on the housing rent when the ranking of the proximity order becomes lower than three. In such a case, the models fail to identify parameters between $\theta^0_{(j)}$ and τ^0 in the first type of generalization and between $\tau^0_{(j)}$ and $\alpha^0_{(j)}$ in the second type of generalization. In contrast, both of the generalized models for Model B1 identify every parameter regardless of the choice of J. Between Model B1 and the corresponding two generalized models, the AICc shows the superiority of the generalized models, whereas the BIC prefers Model B1. Although the model selection remains as an open question, one can conclude that Model B1 holds an advantage to the other models in these applications in the sense that it provides meaningful interpretations, without suffering from serious multicollinearity problem, of the spatial effect of the clustering stations on the housing rent.

3.4. Conclusion

The aim of this paper is to construct an empirical model to estimate the spatial effect of multiple sites that satisfies three general assumptions: (A1) the closer a site, the greater the effect may be, (A2) the impact of a site differs by its characteristics, and (A3) the lower the proximity order of a site, the lower the impact may be. The last assumption (A3) in particular was not considered in previous empirical studies dealing with multiple sites. Thus, two models were estimated, based on the exponential-type and linear-type gravity-base measure, by introducing an additional term, which assigns different weights to the spatial effect of each site depending on its proximity order.

The application was made to housing rent in relation to multiple surrounding train or subway stations in Tokyo. The estimation result is supposed to improve with the number of stations used in the proximity measure under the true functional specification of the spatial effect. However, when the traditional accessibility measure is used in the hedonic model, the prediction power declines as the number of stations is increased in the model. This result suggests that the traditional accessibility measure, which does not account for the third assumption (A3), is not an appropriate model in the context of our application. In contrast, the proposed models solve this problem and obtain better results when a larger r number of stations is included in the models. Although almost all the literature studies analyzing the housing market in Tokyo consider only the distance to the closest station in the hedonic model, the present study shows that the housing rent in Tokyo is influenced by at least the first three closest stations. The result also shows that including more than the first five closest stations in the model does not improve the estimation result.

It was also observed in the application that linear-type proximity measures (Models B0 and its extended models) perform better than exponential-type proximity measures (Models A0 and its extended models) based on the AICc and BIC. One of the advantages of the linear-type proximity measure is its ability to estimate two marginal effects (in terms of distance and of quantitative characteristics) independently. The exponential-type proximity measure assumes a negative correlation between these two marginal effects by the construction of its functional form; hence, it fails to provide a valid interpretation of the result when its assumptions are not true. Further, it fails to yield estimates when the marginal effect of the quantitative characteristics is too small and/or when the spatial effect actually takes a linear form. Among the three linear-type proximity measures (Models B1 and its generalized measures, presented in Appendix E), the choice of the best model remains an open question, based on the AICc and BIC. Nevertheless, the simplest specification of Model B1 is practical in the sense that it provides a clear interpretations about the spatial effect of clustering stations without encountering a multicollinearity problem.

The proposed models are applicable to spatial analyses dealing with various types of multiple sites, such as crime scenes, foreclosures, and neighbor amenities. For each application, the proximity measure needs to be used with appropriate quantitative and qualitative characteristics of sites of interest. For instance, the quantitative characteristics can be the time passed since an incident and the qualitative characteristics can be a type of the incidence such as homicide, robbery or assault, for a study of multiple crime scenes in neighborhood. For the examination of the spatial effect of stores, the quantitative and qualitative characteristics can be replaced by the floor area (or sales) and the type of a store, respectively.

We also suggest that this methodology is worth testing within the context of a polycentric urban structure to examine the possibility of a discounting impact of a city for the lower order proximity. Although these studies use the traditional accessibility measures, one might suspect that surrounding cities have distinct spatial impacts depending on their proximity orders. Some of the studies use commuting time in lieu of the distance measure . Consider a situation in which a high-speed rail was constructed from hometown to another city such that the time distance to the city became shorter than time distances to some of other cities. If the marginal effects of accessibility to the other cities remain the same before and after the construction of the high-speed rail, the traditional accessibility measure may be an appropriate measure to examine the polycentric urban structure. However, if the relative importance of a surrounding city is altered by its proximity order, the use of the traditional accessibility measure results in the biased estimate and therefore the impacts of polycentric cities need to be reexamined with the proposed proximity measures.

3.5. Tables and Figures

Table 3.1. Proximity measures and implications for the spatial effect of multiple sites

		Proximity measure			
		(i) Distance to the closest site	(ii) Number of sites within a range	(iii) Indicator of sites within a range	(iv) Traditional accessibility measure
General assumptions about the special effect of multiple sites					
(A1)	The closer a site, the greater the impact may be.	○	×	×	○
(A2)	The impact may differ by the characteristics of the sites.	○[a]	○[a]	○[a]	○[a]
(A3)	The higher the ranking of proximity of a site, the higher the impact may be.	△[b]	×	△[b]	×

○: The proximity measure addresses the assumption. ×: The proximity measure does not address the assumption. ○[a] : All proximity measures are able to address different impacts of heterogeneous sites by introducing distinct parameters and dummy variables. △[b] : These measures are extreme cases in which no weights are assigned to the effects of any sites except the closest one.

Table 3.2. Assumptions of and potential issues related to proximity variables in the hedonic model

Proximity variable	Assumptions of the functional forms and issues
Distance to the closest site	• Assuming that only the distance to the closest sites matters (although distances to the second and third closest sites may matter). • Overestimating the effect of the closest site because of its positive correlations with the second closest site, the third closest site, and so forth.
Number of sites within a range	• Assuming the same magnitude of spatial effect of sites within a boundary regardless of distances to the sites (although the effect may be greater for a closer site). • Imposing clear-cut neighborhood boundaries (although the effect may be continuously decreasing in distance). • An arbitrary decision on boundaries. • Underestimating or overestimating the effect of a site near the housing or border within the boundary.
Indicator of sites within a range	• Assuming that whether the closest site is located within a boundary matters regardless of the locations of the second closest site, the third closest site, and so forth (although the effect may be greater with a greater number of sites within a boundary). • Assuming the same magnitude of spatial effect for the closest site within a boundary regardless of the distance to the site (although the effect may be greater for a closer site.) • An arbitrary decision on boundaries. • Underestimating or overestimating the effect of the closest site near the housing or border within the boundary.
Traditional accessibility	• Assuming the same weight of importance on all sites regardless of their order of proximity (although people may care more about the closest site than the second closest site). • Overestimating the effect of sites with lower order proximity because of negative correlations between the order of proximity to a site and its significance.

Table 3.3. Previous literature studies using accessibility measures in the hedonic approach

[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Paper	Study area (years of data)	Accessibility measure	Bdy	Distance (zone)	q_z	Sample (zones)	Mth
Osland and Thorsen (2008)	Southwest Norway (1997–2001)	$\tau \log \sum_z q_z e^{\alpha d_{iz}}$, $\tau \log \sum_z q_z^{\gamma} e^{\alpha d_{iz}}$, $\tau \log \sum_z (q_z/Q_z) d_{iz}$, $\tau \log \sum_z q_z^{\gamma} d_{iz}^{\sigma}$,	C	ZtoZ (zip code)	EO	2788 (98)	ML
Osland and Pryce (2012)	Glasgow, Scotland (2007)	$\sum_z \tau q_z^{\gamma} d_{iz}^{\sigma} e^{\alpha d_{iz}}$	*1	PtoZ	Worker	6269 (6501)	GS
Osland (2010)	Southwest Norway (1997–2002)	$\sum_z \tau [q_z^1 \exp\,(\alpha^1 d_{iz}/h)\ + q_z^2 \exp\,(\alpha^2 d_{iz}/h)]^h$	C	ZtoZ (zip code)	Worker	1691 (55)	ML
Giuliano et al. (2010)	Los Angeles, CA	$\sum_z \tau q_z e^{\alpha d_{iz}}$	C	ZtoZ (TAZ)	Job	22,552 (308)	given
Franklin and Waddell (2003)	King County, WA (1995–1998)	$\sum_z \tau q_z e^{\alpha d_{iz}}$	*2	ZtoZ (TAZ)	C/E/I	41,600 (938)	GS
McArthur et al. (2012)	Southwest Norway	$\tau \log \sum_z q_z^{\gamma} e^{\alpha d_{iz}}$	C	ZtoZ (zip code)	Job	4479 (153)	ML
Ahlfeldt (2011)	Berlin, Germany (2000–2008)	$\tau \log \sum_z q_z e^{\alpha d_{iz}}$	C	ZtoZ (VP)	Worker	33,843 (1201)	GS
Ahlfeldt and Wendland (2010)	Berlin, Germany (1881–1936)	$\sum_z \tau q_z e^{\alpha d_{iz}}$	C	ZtoZ (CP)	LandV	1470 (1470)	NLS
Adair et al. (2000)	Belfast Urban Area (1996)	$\sum_z \tau (q_z/Q_z) e^{\alpha d_{iz}}$	*3	ZtoZ (TAZ)	People	2648 (182)	given
Wang and Minor (2002)	Cleveland, OH (1980–2000)	$\sum_z \tau (q_z/Q_z) d_{iz}^{\sigma}$	C	ZtoZ (CT)	Job	193 (193)	given

[1] Paper, [2] Study area and years of data, [3] Accessibility measure: d_{iz} = distance from housing i to zone z, q_z= value of attractiveness of zone z, $Q_z = \sum_z q_z$, parameters = $\tau, \alpha, \gamma, \sigma, h$, [4] Boundary condition: C = censored by study area, *1 = includes extra 60 km, *2 = includes Puget Sound region, *3 = includes 36 extra zones, [5] Distance calculations and zone type: ZtoZ = zone-to-zone, PtoZ = point-to-zone, TAZ = traffic analysis zone, VP = voting precincts, CP = commercial post defined in Bruno Aust (1986), CT = census track [6] q_z (value of attractiveness in zone z): EO = the number of employment opportunities, Worker = the number of workers, Job = the number of jobs, C/E/I = the number of commercial, educational, industrial employment opportunities, LandV = land value, People = the number of people commuting from zone i to zone s, Q_z = attractiveness/access measures of zone s from other areas, [7] Sample size and the number of zones in the study area, [8] Estimation method: ML = maximum likelihood, NL = nonlinear least squares, GS = grid search, given = conducting ordinary least squares with preestimated accessibility parameters.

Table 3.4. Definitions of variables

Variable	Definition
$d_{(j)}$	Distance (miles) to the jth closest station, $s_{(j)}$
$q_{(j)}$	Number of train/subway lines at $s_{(j)}$
$D^1_{(j)}$	New-line dummy, i.e., 1 = if $s_{(j)}$ has a line that does not stop at $s_{(1)\ldots}\ s_{(j-1)}$; 0 = otherwise
$D^0_{(j)}$	1 = if $D^1_{(j)} = 0$, i.e., all lines at $s_{(j)}$ stop at either one of $s_{(1)\ldots}\ s_{(j-1)}$; 0 = otherwise
Rent	Rental price per month (¥10,000 per month)
FSpace	Floor space (square foot)
Bedrooms	Number of bedrooms
FLevel	Floor level
Age	Age of the building (year)
Story	Total number of floor levels in a building
Shop	Number of retail stores within 1 mile
CBD	Distance (miles) to the closest major station: major stations are Shinjuku, Ikebukuro, Shibuya, Shinagawa, Tokyo, Ueno, Musashikosugi
AC	1 = air conditioner equipped; 0 = otherwise
FL1	1 = unit located on the first floor of the building; 0 = otherwise
Corner	1 = unit located at a corner of the building; 0 = otherwise
Propan	1 = propane gas; 0 = otherwise
IH	1 = stove with induction heating equipment; 0 = otherwise
AutoLock	1 = building entrance with an autolock system; 0 = otherwise
Box	1 = apartment with parcel lockers; 0 = otherwise
Apartment1	1 = standard apartment; 0 = otherwise
Terraced	1 = terraced house; 0 = otherwise
Apartment2	1 = luxury apartment; 0 = otherwise
House	1 = family home; 0 = otherwise
PC	1 = prestressed concrete; 0 = otherwise
RC	1 = reinforced concrete; 0 = otherwise
SRC	1 = steel-reinforced concrete; 0 = otherwise
Steel	1 = steel; 0 = otherwise
Wooden	1 = wooden; 0 = otherwise
Other	1 = none of the above structures; 0 = otherwise

Table 3.5. Basic statistics (dependent variable, control variables)

Variable	Mean	SE	Minimum	Maximum
Dependent variable				
Rent	8.96	3.58	4.00	26.50
Independent variable				
FSpace	30.73	15.23	5.00	145.21
Bedrooms	1.34	0.61	1.00	6.00
Flevel	2.96	2.42	1.00	38.00
Age	16.74	10.87	0.00	45.00
Story	4.76	3.67	1.00	99.00
Shop	4.16	4.41	0.00	61.00
CBD	6.09	3.07	0.00	13.13
AC	0.88	0.32	0	1
FL1	0.26	0.44	0	1
Corner	0.38	0.49	0	1
Propan	0.03	0.17	0	1
IH	0.06	0.24	0	1
AutoLock	0.36	0.48	0	1
Box	0.22	0.41	0	1
Apartment1	0.34	0.47	0	1
Terraced	0.00	0.06	0	1
Apartment2	0.66	0.48	0	1
House	0.00	0.05	0	1
PC	0.00	0.05	0	1
RC	0.43	0.49	0	1
SRC	0.07	0.26	0	1
Others	0.01	0.11	0	1
Steel	0.26	0.44	0	1
Wooden	0.22	0.42	0	1

Table 3.6. Basic statistics (distance, number of lines, new-line dummy)

Variable	Mean	SE	Minimum	Maximum
Distance: $d_{(j)}$				
$d_{(1)}$	0.56	0.36	0.01	2.62
$d_{(2)}$	0.93	0.43	0.13	3.06
$d_{(3)}$	1.20	0.49	0.26	3.55
$d_{(4)}$	1.42	0.54	0.38	3.69
$d_{(5)}$	1.59	0.56	0.49	3.85
$d_{(6)}$	1.75	0.60	0.52	4.14
$d_{(7)}$	1.89	0.63	0.60	4.42
$d_{(8)}$	2.03	0.66	0.69	4.65
$d_{(9)}$	2.16	0.69	0.82	4.79
Number of train/subway lines: $q_{(j)}$				
$q_{(1)}$	1.45	0.93	1	10
$q_{(2)}$	1.42	0.97	1	12
$q_{(3)}$	1.38	0.90	1	12
$q_{(4)}$	1.42	0.95	1	12
$q_{(5)}$	1.43	0.93	1	12
$q_{(6)}$	1.46	1.02	1	12
$q_{(7)}$	1.47	1.16	1	12
$q_{(8)}$	1.46	1.15	1	12
$q_{(9)}$	1.49	1.16	1	12
New-line dummy: $D^1_{(j)}$				
$D^1_{(1)}$	1	0	1	1
$D^1_{(2)}$	0.51	0.50	0	1
$D^1_{(3)}$	0.44	0.50	0	1
$D^1_{(4)}$	0.41	0.49	0	1
$D^1_{(5)}$	0.35	0.48	0	1
$D^1_{(6)}$	0.31	0.46	0	1
$D^1_{(7)}$	0.30	0.46	0	1
$D^1_{(8)}$	0.29	0.45	0	1
$D^1_{(9)}$	0.27	0.44	0	1

Table 3.7. Model A0: Traditional accessibility measure

	[7-1]	[7-2]	[7-3]	[7-4]	[7-5]
J =	1	2	3	5	9
Parameters in the proximity measure					
τ_1	0.39***	0.34***	0.29***	0.24***	0.26***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)
α_1	−1.52***	−1.92***	−1.71***	−1.54***	−2.24***
	(0.19)	(0.19)	(0.26)	(0.37)	(0.68)
τ_0		-1.15	0.04	0.03	0.02
		(2.00)	(0.03)	(0.02)	(0.01)
α_0		-7.06	0.00	-0.02	-0.06
		(6.25)	(0.37)	(0.31)	(0.18)
X					
FSpace	0.21***	0.21***	0.21***	0.21***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bedrooms	−0.41***	−0.42***	−0.42***	−0.42***	−0.42***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
FLevel	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	−0.05***	−0.05***	−0.05***	−0.05***	−0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Story	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CBD	−0.16***	−0.15***	−0.15***	−0.15***	−0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AC	0.4***	0.41***	0.41***	0.41***	0.41***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
FLevel1	−0.11***	−0.11***	−0.11***	−0.12***	−0.11***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Corner	−0.06**	−0.05*	−0.05*	−0.05*	−0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AutoLock	0.27***	0.27***	0.27***	0.27***	0.28***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Box	0.65***	0.65***	0.65***	0.65***	0.65***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Log likelihood	−23,630	−23,641	−23,658	−23,672	−23,700
AICc	47,352	47,379	47,412	47,441	47,497
BIC	47,700	47,742	47,776	47,804	47,861
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in the traditional accessibility measure, Model A0. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of building-structure dummies (*PC*, *RC*, *SRC*, *Others*, *Steel*, *Wooden*), apartment-type dummies (*Apartment1*, *Terraced*, *Apartment2*, *House*), and three variables that do not have significant effects (*Shop*, *Propan* and *IH*) are not shown in the table.

Table 3.8. Model B0

	[8-1]	[8-2]	[8-3]	[8-4]	[8-5]
J =	1	2	3	5	9
τ_1	0.16***	0.10***	0.07***	0.06***	0.04***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
α_1	−0.48***	−0.29***	−0.17***	−0.09***	−0.03***
	(0.09)	(0.04)	(0.04)	(0.02)	(0.02)
τ_0		0.15***	0.13***	0.06***	0.04**
		(0.05)	(0.04)	(0.02)	(0.02)
α_0		0.16	0.03	0.03	0.00
		(0.15)	(0.05)	(0.04)	(0.01)
ω^0		−0.48***	−0.29***	−0.14**	−0.02
		(0.11)	(0.08)	(0.06)	(0.04)
R^2	0.8788	0.8787	0.8776	0.8772	0.8766
Log likelihood	−23,607	−23,612	−23,675	−23,699	−23,736
AICc	47,307	47,323	47,449	47,496	47,569
BIC	47,655	47,694	47,820	47,867	47,940
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows ordinary least squares estimates using a different number of closest stations (*J*) in Model B0. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, ***X***, are not shown in the table.

Table 3.9. Model A1

	[9-1]	[9-2]	[9-3]	[9-4]	[9-5]
J =	1	2	3	5	9
τ^1	0.39***	0.42***	0.43***	0.44***	0.43***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
α^1	-1.52***	-1.53***	-1.49***	-1.43***	-1.43***
	(0.19)	(0.16)	(0.16)	(0.15)	(0.17)
τ^0		-0.79*	-0.41	-0.24	-0.32
		(0.41)	(0.55)	(0.24)	(0.22)
α^0		-3.36***	-2.16	-1.57**	-1.92***
		(0.65)	(2.00)	(0.70)	(0.50)
θ^1		-2.27***	-2.23***	-1.79***	-1.82***
		(0.82)	(0.68)	(0.52)	(0.56)
θ^0			-0.49	0.07	-0.42
			(2.46)	(0.51)	(0.39)
Log likelihood	–23,630	–23,606	–23,603	–23,596	–23,598
AICc	47,352	47,310	47,306	47,292	47,296
BIC	47,307	47,230	47,208	47,198	47,200
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in Model A1. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, ***X***, are not shown in the table.

Table 3.10. Model B1

	[10-1]	[10-2]	[10-3]	[10-4]	[10-5]
$J =$	1	2	3	5	9
τ^1	0.16***	0.16***	0.18***	0.19***	0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
α^1	−0.48***	−0.52***	−0.56***	−0.57***	−0.55***
	(0.09)	(0.08)	(0.07)	(0.11)	(0.14)
τ^0		0.06	0.03	0.01	0.02
		(0.05)	(0.05)	(0.07)	(0.06)
α^0		0.30**	0.29**	0.24	0.28
		(0.14)	(0.14)	(0.24)	(0.23)
ω^0		−0.45***	−0.43***	−0.40*	−0.45**
		(0.11)	(0.12)	(0.22)	(0.19)
θ^1		−2.77***	−3.22***	−2.57***	−2.62***
		(0.88)	(0.78)	(0.59)	(0.68)
θ^0			−2.48	−1.10	−1.99
			(1.99)	(2.17)	(3.12)
θ^2			−1.14	−0.71	−1.18
			(0.70)	(1.10)	(1.03)
Log likelihood	−23,607	−23,565	−23,552	−23,547	−23,548
AICc	47,307	47,230	47,208	47,198	47,200
BIC	47,655	47,609	47,601	47,591	47,594
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in Model B1. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, ***X***, are not shown in the table.

Figure 3.1. Train and subway stations around Tokyo's 23 wards in 2011.

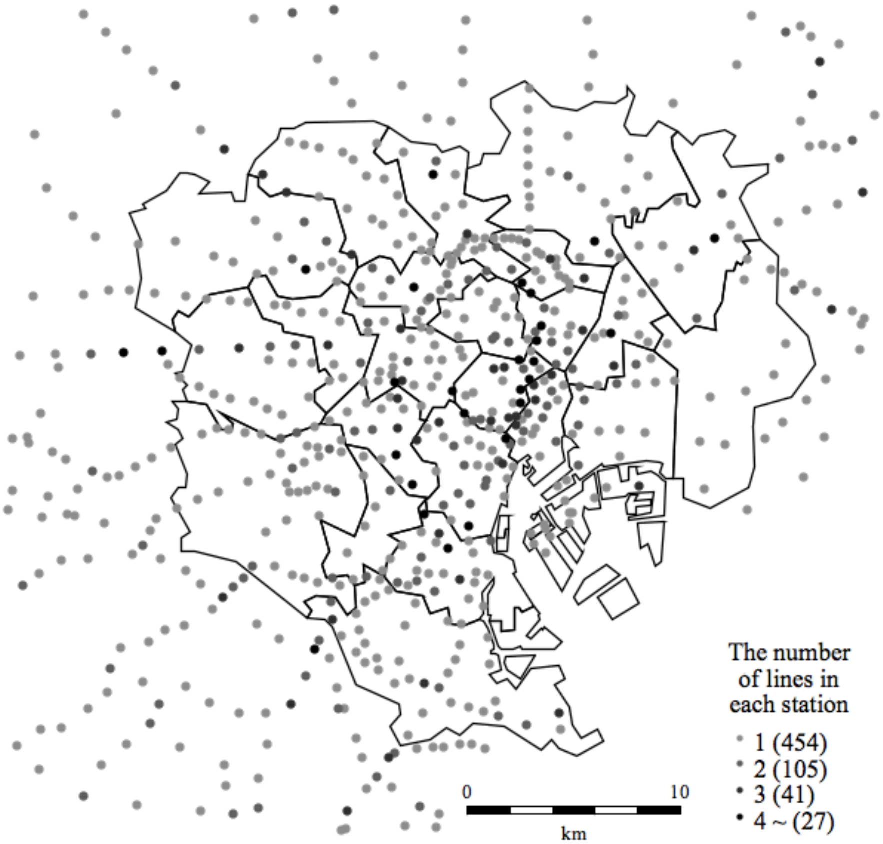
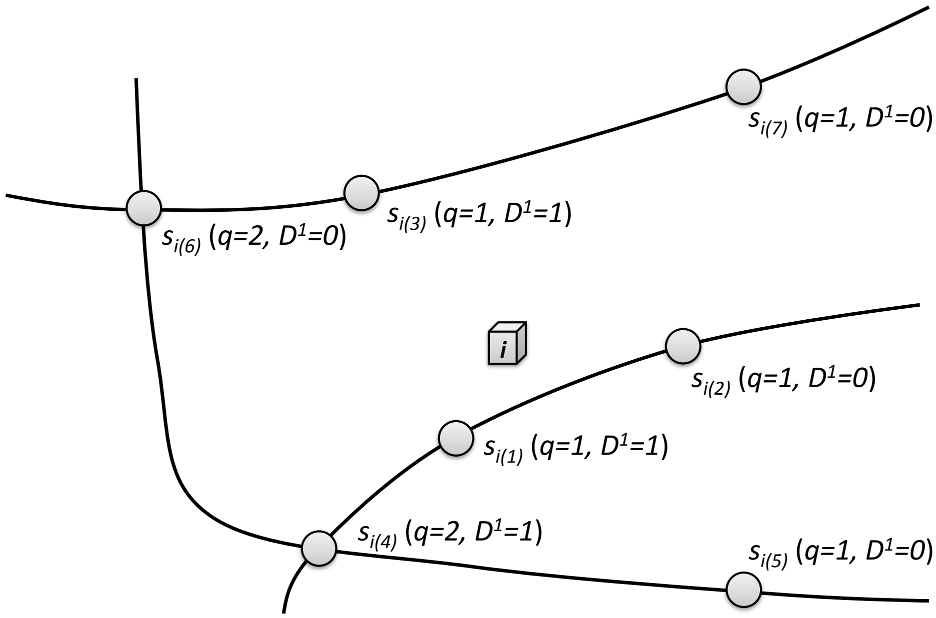
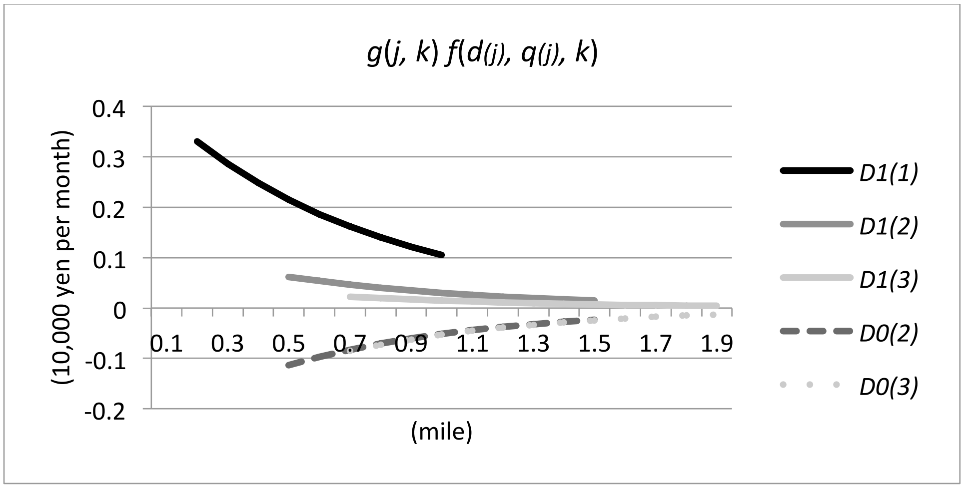


Figure 3.2. Quantitative (q) and qualitative (D^1) characteristics



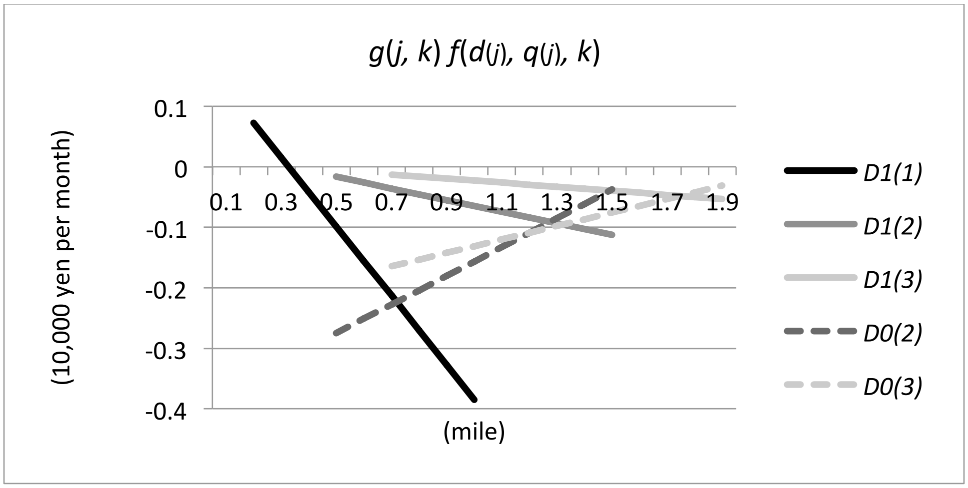
$s_{i(j)}$ indicates the jth closest station from housing i. q is a number of lines and D^1 is a new-line dummy. The closest station, $s_{i(1)}$, has one line, i.e. q = 1, and it is the closest station from housing i to take the line, i.e. D^1 = 1. The second closest station, $s_{i(2)}$, also has one line, i.e. q=1, while this line leads to the closer station which is $s_{i(1)}$, i.e. D^1 = 0; in other words, the resident of housing i can go to $s_{i(1)}$ to take the line in stead of going to $s_{i(2)}$. The new-line dummy for the third closest station $s_{i(3)}$ is one because it is the closest station from housing i to take the line that leads to the station. On the other hand, the new-line dummy for the sixed closest station, $s_{i(6)}$, is zero because the resident can go to closer stations, $s_{i(3)}$ and $s_{i(4)}$, to take all lines that lead to the station.

Figure 3.3.   Model A1



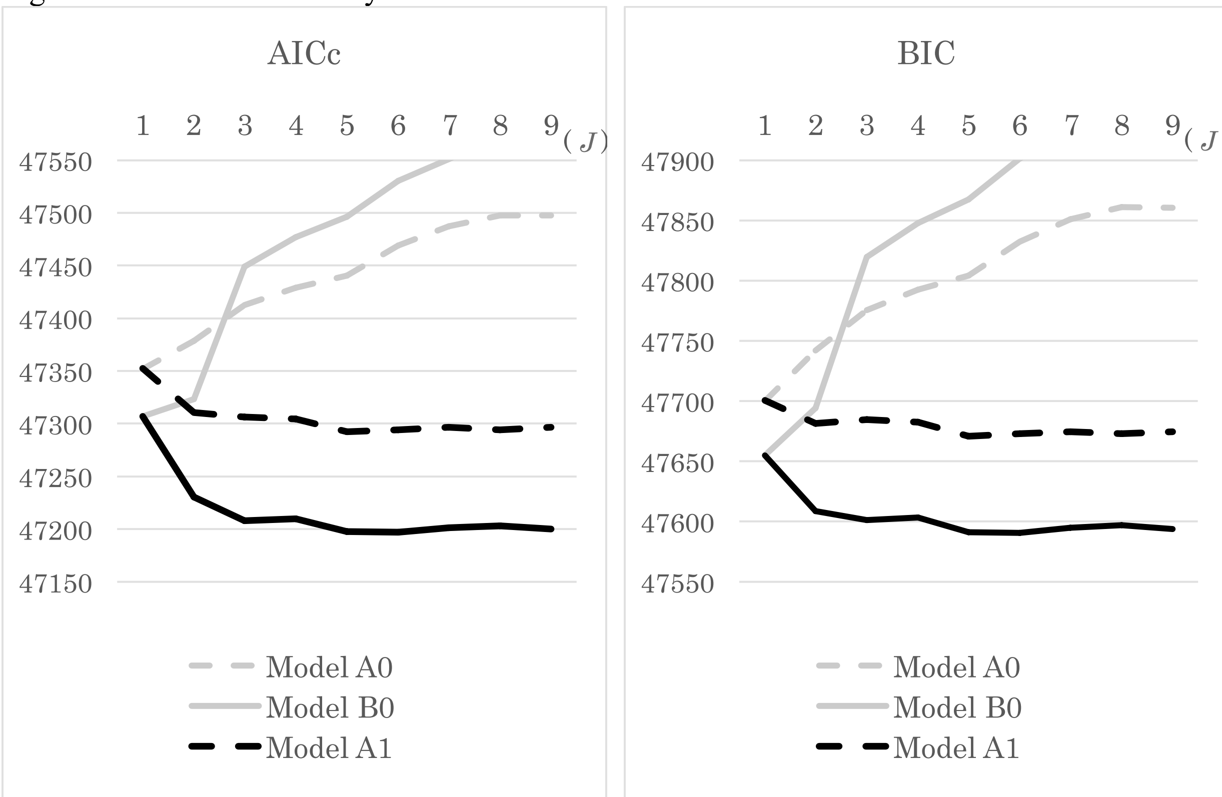
This figure illustrates $g(.)f(.)$ in Model A1 with respect to distance, based on the result in [9-4] of table 3.9. The quantitative value $q_{(j)}$, i.e., the number of lines, is fixed at one. Each line is drawn between the 10th percentile and the 90th percentile of distances to stations with a corresponding proximity order. Note that the levels of $g(.)f(.)$ illustrated in this figure are not comparable between different proximity orders because $c_{(j)}$s are not included in these measures. $D^1_{(1)}$ is the closest station, $D^1_{(2)}$ is the second closest station with a new line, $D^1_{(3)}$ is the third closest station with a new line, $D^0_{(2)}$ is the second closest station without a new line, and $D^0_{(3)}$ is the third closest station without a new line.

Figure 3.4.   Model B1



This figure illustrates $g(.)f(.)$ in Model B1 with respect to distance, based on the result in [10-4] of table 3.10. The quantitative value $q_{(j)}$, i.e., the number of lines, is fixed to one. Each line is drawn between the 10th percentile and the 90th percentile of distances to stations with a corresponding proximity order. Note that the levels of $g(.)f(.)$ illustrated in this figure are not comparable between different proximity orders because $c_{(j)}$s are not included in these measures. $D^1_{(1)}$ is the closest station, $D^1_{(2)}$ is the second closest station with a new line, $D^1_{(3)}$ is the third closest station with a new line, $D^0_{(2)}$ is the second closest station without a new line, and $D^0_{(3)}$ is the third closest station without a new line.

Figure 3.5. Akaike and Bayesian information criteria.



Appendix A: Collective Decision-Making Time in Condominium Reconstruction

Here, we report on a simple regression analysis conducted to examine relationships between the number of owners of a condominium and the collective decision-making time. We use data provided by Meno (2004) and from a website[53] listing recently completed condominium reconstruction projects. The specification for the regression analysis is as follows:

$$\ln(CDMtime)_i = \alpha_0 + \alpha_1 \ln(UNITold)_i + \alpha_2 FAM_i + \alpha_3 UNITM_i + \alpha_4 SELFHAT_i + \alpha_5 \ln(AGEstart)_i + \alpha_6 TOKYO_i + \varepsilon_i, \tag{A1}$$

where subscript i indicates the ith condominium, *CDMtime* is the duration of the collective decision-making process surrounding reconstruction (in months),[54] *UNITold* is the number of units in the previous condominium, *FAM* is the floor area of the new condominium divided by the floor area of the previous condominium, *UNITM* is the number of units in the new condominium divided by the number of units in the old condominium, *AGEstart* is the number of years that have passed between the time the old condominium was built and the time the first official meeting on the reconstruction takes place, *TOKYO* is a dummy variable indicating a condominium located in the Tokyo prefecture, and ε is an error term.

Finally, *SELFHAT* is the expected value for a dummy variable, *SELF*, which is assigned 0 if a developer is involved in the decision-making process and 1 if residents plan and carry out the procedure themselves. The decision-making procedure can be better managed without the support of others when a collective action problem is not serious and thus requires less time for collective action. To take into consideration such an endogenous issue, we first use a probit estimate regressing *SELF* on *FAM*, *UNITM*, ln(*AGEstart*), *TOKYO*, and *START* (the starting year of collective action) to obtain *SELFHAT*, the fitted value of *SELF*.

According to the basic statistics in table A1, reconstruction takes place in 39.52 years on average (ranging from 19 to 74 years) after the completion of the condominium, and the decision-making process takes 6.03 years on average (from 0.6 to 18.6 years) to achieve consensus on reconstruction. When looking at *FAM* and *UNITM*, we observe that new condominiums have a larger total floor area as well as a larger number of units after reconstruction. In a newly reconstructed condominium, the total floor area and the number of units are increased on average by 176 and 79%, respectively. In fact, in only one condominium was the total floor area reduced

[53] The URL of the website from which we collected the data on condominium reconstructions in August 2011 is http://www.manshon.jp/tatekae/ta_jirei_index.html.

[54] The duration of collective decision making regarding reconstruction, *CDMtime*, is the number of years between the time when the first official meeting on reconstruction is held and the time when a consensus on reconstruction is reached. However, some data lack information on when the consensus is reached. To cope with this problem, we obtain the time to reach consensus by subtracting the estimated number of years for construction (the number of years required to tear down the old condominium and build the new one) from the time the new condominium is completed. The number of years for construction is estimated with coefficients obtained by regressing reconstruction time on the total floor area of the new condominium and the age of the old condominium, with samples having information on the duration of reconstruction.

after reconstruction. With the total floor area of a condominium expanded, owners can benefit from having more space in their own units, and they can sell extra units to cover the reconstruction cost, which will enable them to achieve consensus more easily.

The probit estimate of *SELF* is shown in column [A2-1] of table A2. The coefficient of ln(*UNITold*) has a negative sign at the 5% significance level. This indicates that the collective action regarding reconstruction is more likely to be well managed without involving a third party if the number of property owners of the condominium is not large. Regarding other variables, only *TOKYO* shows a significant effect, at the 15% significance level, on *SELF*. This implies that collective decision making in Tokyo is more difficult than in other prefectures, and therefore tends to involve a developer to manage the process efficiently.

Columns [A2-2] and [A2-3] in table A2 show estimation results for equation (A1). In addition to ordinary least squares (OLS) estimates, we have conducted a truncated regression because *CDMtime* is truncated in such a way that we do not observe the condominiums whose collective decision making is still in progress. The coefficients of ln(*UNITold*) show positive signs and they are statistically significant, verifying that an increase in the number of property owners requires more time to achieve consensus on reconstruction. In concrete terms, if the number of units doubles, the time needed for collective decision making is extended by about 30%.

Regarding the other variables, the coefficients of *FAM* have positive signs. This may be because, as part of the decision-making process, it takes more time to consider the method by which the surplus floor area will be used and operated. The coefficients of ln(*AGEstart*) show that the time needed for collective decision making is reduced by about 45% if the age of the condominium is doubled. Although the significance levels are not strong (ranging from 10 to 15%), this result implies that property owners hasten their decision making on reconstruction when their condominiums are more dilapidated. The coefficients of *SELFHAT* have remarkably negative effects on decision-making time, as expected, although their signs are not significant because of the presence of multicollinearity.[55] Finally, coefficients of the variable *TOKYO* indicate that the collective decision-making time is about 47% longer in Tokyo than in other prefectures. Intuitively, this result makes sense because people in such a large city have various backgrounds and interests, which can complicate the process of collective action. Moreover, people relocate more frequently in Tokyo; thus, they are likely to have less incentive to contribute to community relations' activities.[56]

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[55]Note that when we use *SELF* in Equation (A1) instead of the fitted value, the coefficients are −0.6623, at the 5% significance level, in the truncated model and −0.6609, at the 10% significance level, in the OLS estimate.

[56]According to a survey conducted by the Ministry of Land, Infrastructure, Transport and Tourism in 2005, neighbor relationships are tenuous in metropolitan areas relative to local regions; about 28% of the population in local regions have no or almost no relationships with neighbors, whereas this percentage increases to 45% in metropolitan areas. As the two main reasons for these shallow relationships among neighbors, the interviewees living in the metropolitan areas reported that (1) they are absent from home during the daytime, and (2) residents are rapidly replaced. The report (in Japanese) is available at http://www.mlit.go.jp/hakusyo/mlit/h17/hakusho/h18/html/H1022100.html.

If owners of condominiums are aware of the future reconstruction problem in advance, they may start collective action at an earlier stage to carry out the reconstruction at the optimal timing. To examine this issue, we regressed ln(*AGEstart*) on ln(*UNITold*), *FAM*, and *TOKYO*. The results are shown in column [A2-4]. The number of units did not significantly influence the timing of the collective action, which ensures that the collective action is not driven by the property value-maximizing behaviors of condominium owners. These results verify that an increase in the number of owners of a condominium lengthens the collective decision-making process involved in reconstruction.

Table A1: Descriptive statistics for 64 cases of condominium reconstruction in Japan.

Variable	Definition	Minimum	Median	Maximum	Mean
CDMtime	Months spent on collective decision making	0.6	4.9	18.6	6.03
YEARold	Year when the construction of a previous condominium was completed	1926	1962	1981	1961.49
YEARnew	Year when the reconstruction of a new condominium was completed	1975	2004	2012	2001.01
START	Year when the first meeting on the reconstruction was held	1969	1992.4	2008.5	1994.73
RecAGE	Number of years between the year of completion of a new and a previous condominium	19	38	74	39.52
AGEstart	Number of years between the year when a previous condominium was completed and the year when residents began to discuss reconstruction	13	33	59.5	33.66
UNITold	Number of housing units in a previous condominium	16	62.5	368	89.19
UNITnew	Number of units in a new condominium	20	96.5	644	150.71
FAold	Floor area (m^2) of a previous condominium	880	3,400	18,511	4,737
FAnew	Floor area (m^2) of a new condominium	1,166	9,274	57,337	13,439
FAM	Ratio of increase in floor area after the reconstruction	0.82	2.62	6.34	2.76
UNITM	Ratio of increase in the number of units after the reconstruction	0.71	1.63	4.2	1.79
SELF	Dummy variable indicating that a reconstruction was conducted by residents (without the support of a developer)	0	0	1	0.09
TOKYO	Dummy variable indicating a condominium is located in the Tokyo prefecture	0	1	1	0.58

Source: Meno (2004), and a website listing past reconstructions (http://www.manshon.jp/tatekae/ta_jirei_index.html).

Table A2: Estimations of the collective decision making time in reconstruction.

	[A2-1]	[A2-2]	[A2-3]	[A2-4]
Model:	Probit	Truncated	OLS	OLS
Dependent variable:	*SELF*	ln(*CDMtime*)	ln(*CDMtime*)	ln(*AGEstart*)
ln(*UNITold*)	−1.3421**	0.2938**	0.2954**	0.0166
	(0.5410)	(0.1262)	(0.1324)	(0.0465)
FAM	−0.1357	0.1864**	0.1869*	0.0303
	(0.2500)	(0.0911)	(0.0957)	(0.0435)
UNITM		−0.0069	−0.0047	
		(0.1221)	(0.1282)	
TOKYO	−0.8876†	0.4724***	0.4705**	0.1357*
	(0.5546)	(0.1814)	(0.1906)	(0.0751)
ln(*AGEstart*)	0.3724	−0.4417*	−0.4469†	
	(1.0147)	(0.2623)	(0.2759)	
SELFHAT		−0.5460	−0.5330	
		(0.7041)	(0.7403)	
START	−0.0220			
	(0.0389)			
LAMBDA		0.6681***		
		(0.0511)		
CONSTANT	47.1534	1.0562	1.0598	1.0598
	(75.5879)	(1.0535)	(1.1098)	(1.1098)
Observations	64	64	64	64
R^2			0.3460	0.3460
Log likelihood	−14.25	−64.73		

Notes: The symbols ***, **, *, and † indicate statistical significance at the 1, 5, 10, and 15% levels using two-tailed tests. Figures in parentheses are robust standard deviations. OLS: ordinary least squares.

Appendix B: Redevelopment Model of a Condominium

The price of the condominium at time t, P_t, is the expected net present value of the discounted future rent, taking future reconstruction into consideration. The price of the condominium at time t, P_t, is then

$$P_t = E_t\left[\int_t^{T_1} R_s e^{-r(s-t)} ds + \sum_{m=1}^{\infty} \int_{T_m}^{T_{m+1}} R_s^m e^{-r(s-t)} ds - C_{T_m} e^{-r(T_m - t)}\right], \quad \text{(B1)}$$

where R_s is the rent of the condominium unit at time s, r is a constant discount rate, C_{T_m} is the reconstruction-related costs, T_m is the timing of the mth reconstruction, and R_s^m is the rent at time s (after the mth reconstruction).

In terms of social optimality, the value of the condominium is maximized through the planning and execution of the reconstruction. We assume that the reconstruction-related costs, C_{T_m}, and the rental value of a newly reconstructed condominium, $R_{T_m}^m$, will remain constant over time. The price of a newly rebuilt condominium, P_{T_m},[57] is then equal for all m under the optimal decisions of the community. Hereafter, we can relate C_{T_m}, $R_{T_m}^m$, and the optimal P_{T_m} to C, R^n, and P^{n^*}, respectively. Thus, we can rewrite the maximization problem for the timing of reconstruction as follows:

$$P_t^* = \max_{T_1} \int_s^{T_1} R_s e^{-r(s-t)} ds + \left(P^{n^*} - C\right) e^{-r(T_1 - t)}. \quad \text{(B2)}$$

The necessary condition for this problem is

$$R_{T_1^*} = r\left(P^{n^*} - C\right), \quad \text{(B3)}$$

where T_1^* is the optimal timing of the first reconstruction and $R_{T_1^*}$ is the rent (before the first reconstruction) at the time of the optimal reconstruction. The optimal timing for a reconstruction is when the rent becomes as low as the opportunity cost of postponing the reconstruction, which equals the cost of interest on the net capital gain accrued from the reconstruction.

However, as discussed, owners of Japanese condominiums rarely achieve an optimal agreement because of the difficulty of the collective action process. We may then assume that reconstruction is usually delayed from the optimal timing. The price change from the expected delay of the next reconstruction by ΔT from the optimal timing T_1^* is then[58]

$$\frac{\partial P_t}{\partial \Delta T} = -\left[R_{T_1^*} - R_{(T_1^* + \Delta T)}\right] e^{-r(T_1^* - t + \Delta T)} < 0. \quad \text{(B4)}$$

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[57]Note that the prices immediately after reconstruction and after an optimal reconstruction are the same as long as we expect every reconstruction to be carried out optimally in the future.

[58]In equation (A5), we assume that only the first forthcoming reconstruction is delayed. If instead we assume that every reconstruction in the future will be equally delayed, the differentiation is as follows:

$$\frac{\partial P_t}{\partial \Delta T} = -\left[R_{T_1^*} - R_{(T_1^* + \Delta T)}\right] \frac{e^{-r(T_1^* - t + \Delta T)}}{1 - e^{-r(T_1^* - t + \Delta T)}} \leq 0.$$

This assumption makes the effects of the reconstruction delay more strongly negative than in equation (5), but it does not change any implications of the following discussion.

Furthermore, the price of the condominium depreciates more when the cost, one of the reconstruction-related cost factors, is higher:

$$\frac{\partial P_t}{\partial C} = -e^{-r(T_1^* - t + \Delta T)}. \tag{B5}$$

Equations (B4) and (B5) show that the condominium price decreases as the expected delay in its future reconstruction becomes longer and as the construction-related costs become larger. By differentiating the price rate of the time change, $\widehat{P_t}\left(\equiv \frac{dP_t}{dt}/P_t\right)$,[59] with respect to ΔT and C, we can predict that the expected delay in future reconstruction and the increase in the cost will accelerate the deterioration of the price:

$$\frac{\partial \widehat{P_t}}{\partial \Delta T} = -\frac{R_t}{(P_t)^2}\left[R_{T_1^*} - R_{(T_1^*+\Delta T)}\right]e^{-r(T_1^* - t + \Delta T)} < 0, \tag{B6}$$

$$\frac{\partial \widehat{P_t}}{\partial C} = -\frac{R_t}{(P_t)^2} e^{-r(T_1^* - t + \Delta T)}. \tag{B7}$$

[59]Differentiating P_t in equation (B1) with respect to t yields

$$\frac{dP_t}{dt} = E_t\left[-R_t + \int_t^{T_1} R_s e^{-r(s-t)} ds + r\sum_{m=1}^{\infty}\int_{T_m}^{T_{m+1}} R_s^m e^{-r(s-t)} ds - C_{T_m} e^{-r(T_m - t)}\right]$$
$$= -R_t^0 + rt;$$

hence, the price of the time change rate is

$$\widehat{P_t}\left(\equiv \frac{dP_t}{dt}/P_t\right) = -\frac{R_t}{P_t} + r.$$

Appendix C. Proofs

Case (a)

Proof of (13). By inserting $\theta_B^k = 0$ into equation (2.12), we obtain $|\alpha^k| = \theta_A^k \tau^k$. Therefore, $|\alpha^k| > 0$ if and only if $\theta_A^k \tau^k > 0$. Because all hidden parameters are nonnegative, $|\alpha^k| > 0$ if and only if $\theta_A^k > 0$ and $\tau^k > 0$ for all k. ■

Case (b)

Proof of (14) to (16). $\tau^k = \tau^l$ for all k and l implies that $\tau^k = \tilde{\tau}$ for all k, where $\tilde{\tau}$ is the mean effect of all event types under complete information. Inserting $\tau^k = \tilde{\tau}$ into equation (2.11) yields $|\alpha^k| = \left(\theta_A^k + \theta_B^k\right)\tilde{\tau}$. Because all hidden parameters are nonnegative, $|\alpha^k| > 0$ implies $\left(\theta_A^k + \theta_B^k\right) > 0$ and $\tau^k = \tau^l = \tilde{\tau} > 0$ for all l. Suppose some m exists such that $|\alpha^m| > 0$; then $\tilde{\tau} > 0$. Given that $\tilde{\tau} > 0$, $|\alpha^k| > 0$ if and only if $\left(\theta_A^k + \theta_B^k\right) > 0$. By comparing the coefficients of the two event types, we have $|\alpha^k| - |\alpha^l| = \left(\theta_A^k + \theta_B^k - \theta_A^l - \theta_B^l\right)\tilde{\tau}$. When some m exists such that $|\alpha^m| > 0$, because $\tilde{\tau} > 0$, $|\alpha^k| > |\alpha^l|$ if and only if $\theta_A^k + \theta_B^k > \theta_A^l + \theta_B^l$. ■

Case (c)

Proof of (17). By taking a derivative of equation (2.12) with respect to τ^k, we have;

$\frac{\partial|\alpha^k|}{\partial\tau^k} = \left(1 + \frac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k}\right) + \frac{\partial\theta_B(\theta_A^k)}{\partial\theta_A^k}\frac{\partial\theta_A(\tau^k)}{\partial\tau^k}\tilde{\tau} + \theta_B^k\frac{\tilde{\tau}}{\partial\tau^k}$, which is strictly larger than zero,

based on the assumptions. Therefore, $|\alpha^k| > |\alpha^l|$ implies $\tau^k > \tau^l$. When $\tau^k > \tau^l$, we have the following four possibilities: 1) $\theta_A^l > 0$ and $\theta_B^k > 0$, 2) $\theta_A^l > 0$ and $\theta_B^k = 0$, 3) $\theta_A^l = 0$ and $\theta_B^k > 0$, and 4) $\theta_A^l = 0$ and $\theta_B^k = 0$. From these assumptions, the first case (1) implies $\theta_A^k < \theta_A^l$ and $\theta_B^k > \theta_B^l$, and the second case (2) implies $\theta_A^k < \theta_A^l$ and $\theta_B^k = \theta_B^l = 0$. However, the third (3) and fourth (4) cases yield $|\alpha^k| = |\alpha^l| = 0$, which contradicts the initial assumption, $|\alpha^k| > |\alpha^l|$. Thus, $\tau^k > \tau^l$ implies $\theta_A^k < \theta_A^l$ and $\theta_B^k \geq \theta_B^l$. ■ Proof of (18). $|\alpha^l| = 0$ requires $\theta_A^l = 0$ or $\tau^l = 0$. Because $|\alpha^k| > |\alpha^l|$, $0 \leq \theta_A^k < \theta_A^l$; thus, $\theta_A^l \neq 0$ and $\tau^l = 0$.■ Proof of (19). Suppose some m exists such that $|\alpha^m| = 0$. Because $\tau^k = \tau^l > 0$ implies $\theta_A^k = \theta_A^l > 0$ and $\theta_B^k = \theta_B^l$, it is sufficient to show that $|\alpha^k| = |\alpha^l| > 0$ implies $\tau^k = \tau^l > 0$. First, suppose that $\tau^k \neq \tau^l$; then because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| \neq |\alpha^l|$, which contradicts $|\alpha^k| = |\alpha^l|$. Second, suppose that $\tau^k = \tau^l = 0$; then $\theta_B^k\tilde{\tau} = \theta_B^l\tilde{\tau} > 0$, implying that $\theta_B^k = \theta_B^l > 0$ and $\tilde{\tau} > 0$. Because θ_B^k is not decreasing in τ^k, $\theta_B^m > 0$ for all m; thus, $|\alpha^m| > 0$ for all m. This contradicts $|\alpha^m| = 0$ for some m.■ Proof of (20). By equation (2.18), $|\alpha^m| > |\alpha^k| = 0$ implies that $\tau^k = 0$, $\theta_A^k = \theta_A(0)$. Because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| = |\alpha^l|$ implies $\tau^k = \tau^l = 0$; thus, $\theta_A^k = \theta_A^l = \theta_A(0)$ and $\theta_B^k = \theta_B^l$.■ Proof of (2.21). Because $\tau^k = \tau^l$ implies $\theta_A^k = \theta_A^l$ and $\theta_B^k = \theta_B^l$, it is sufficient to show that $\nexists m$ such that $|\alpha^m| > |\alpha^k| = |\alpha^l| > 0$ implies $\tau^k = \tau^l > 0$. First, suppose that $\tau^k \neq \tau^l$; then because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| \neq |\alpha^l|$, which contradicts $|\alpha^k| = |\alpha^l|$. Second, suppose that $\tau^k = \tau^l = 0$. Because $|\alpha^k| = |\alpha^l| > 0$, then $\tilde{\tau} > 0$ and $\theta_B^k = \theta_B^l > 0$; thus, it requires some m such that $\tau^m > 0$ to have $\tilde{\tau} > 0$. Because $|\alpha^m|$ is strictly increasing in τ^m, it contradicts that $\nexists m$ such that $|\alpha^m| > |\alpha^k| = |\alpha^l|$.■

Appendix D: Traditional Accessibility Measure in Hedonic Model

This appendix discusses the accessibility measure used in the hedonic analysis in the previous literature studies. Table 3 summarizes the most of the following discussion. The hedonic model accompanied with a traditional zone-to-zone accessibility measure is described as:

$$y_i = A(\{d_{zz'}, q_{z'}\}_{z' \in \mathbf{Z}}) + \mathbf{X}_i \boldsymbol{\beta} + e_i, \tag{D1}$$

where y_i is a property value of housing $i \in \{1, \dots, N\}$ in a region $z \in \{1, \dots, Z\}$, $A(.)$ is an accessibility measure, $\mathbf{X}_i$ is a vector containing a constant value and control variables affecting y_i, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and e_i is an error term.

The accessibility measure $A(.)$ is a function of distances from the region of a house i to all regions $\{d_{zz'}\}_{z' \in \mathbf{Z}}$ in the study area and of regional characteristics $\{q_{z'}\}_{z' \in \mathbf{Z}}$. A distance of two regions can be calculated as a Euclidian distance between central points of the two regions, or it can be calculated based on the transportation time and fees between major stations in two regions instead. Typically, the number of employees and jobs are used as the values for the regional characteristics.

Among various accessibility measures that have been examined in existing studies, types of gravity-based formula, introduced by Hansen (1959), are recognized to perform better than other types of accessibility measures in terms of the predicting power and the flexibility of functional form. The most commonly used gravity-based accessibility measure is a negative-exponential type, described as,

$$A_i = \sum_{z' \in \mathbf{Z}} \tau q_{z'} e^{\alpha d_{zz'}} \tag{D2}$$

where τ and α are parameters to be estimated. The previous literatures report positive τ and negative α, that is, the region with more job opportunities has a positive influence on the housing value in surrounding regions, while the impact becomes lower with the distance. Various extensions of the measure (D2) are possible as long as parameters can be identified. The other typical type of gravity-base accessibility measure is an inverse-power type; $A_i = \tau \sum_{z' \in \mathbf{Z}} q_{z'} d_{zz'}^{\lambda}$ where λ takes a negative sign (Song, 1996; Saize et al., 2011). The weighted sum of foreclosures used in Campbell et al. (2011) is equivalent to the inverse-power type of accessibility measure where they impose $q_{z'} = 1$ and $\lambda = -1$.

A boundary condition is one of issues of the traditional accessibility measure. Since regions by which the accessibility measure is computed are censored in many literature studies, the measure tends to be underestimated near the boundary of the study area, known as a boundary or edge effects. Two approaches have been adapted to address this issue. One is to include surrounding regions to compute accessibility measures for the study area of interest. However, the accessibility measure still tends to be overestimated in the center of study area even under such a treatment as long as the entire area is used to construct the measure. The other way is to limit the regions from each housing to compute the accessibility measure (Gjestland et al., 2014).

Given the nonlinearity of the accessibility measure, three approaches have been used to estimate the hedonic model in the previous studies. The first approach is the maximum likelihood method or nonlinear regression, which is practical in the sense that the estimation can be done by a single step and also reliable because it ensures validity of the functional specification by obtaining a result. One can suspect that the main reason that some studies avoid using this approach is partly due to the inappropriate specification of the model, which prevents the estimation from identifying parameters in the measure. The second approach, the grid-search method, may help to obtain an estimation result in the presence of the identification problem. In this method, numbers of linear regressions with various combinations of parameters are employed to find the one that yields the highest likelihood or R-squared. Accordingly, the results do not provide standard errors of these parameters and thus, it is difficult to discern the stability of the parameters. The third approach is to assign specific values to parameters in the nonlinear terms and then, to run the ordinary least squares to estimate the hedonic model. These values are typically taken from other studies or estimated prior to the hedonic estimation.

Appendix E: Additional Estimations

This appendix discusses some additional results for generalized specifications of proposing models. The extended models of Model A1 and their estimation results are demonstrated, followed by those of Model B2. First, as extended specifications of Model A1, hedonic functions to be estimated are the following two models;

Model A2

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^{1} \theta_{(j)}^{1} \tau^{1} q_{i(j)} e^{\alpha^{1} d_{i(j)}} + D_{i(j)}^{0} \theta_{(j)}^{0} \tau^{0} q_{i(j)} e^{\alpha^{0} d_{i(j)}} + c_{(j)}$$

Model A3

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^{1} \tau_{(j)}^{1} q_{i(j)} e^{\alpha_{(j)}^{1} d_{i(j)}} + D_{i(j)}^{0} \tau_{(j)}^{0} q_{i(j)} e^{\alpha_{(j)}^{0} d_{i(j)}} + c_{(j)}$$

In Model A2, $f(.)$ is the same as $f(.)$ in Model A1, whereas $g(.)$ is generalized in such a way that the weights are free from functional restrictions. Model A3 eases the functional restriction even farther such that all parameters in $f(.)$ can be different by proximity orders and types of stations. Accordingly, the number of parameters increases with J in the both extended models.

Table E1 describes estimation results for Model A2. The results of the model with J = 4 and more are not shown in the table because these maximum likelihood estimates do not converge. It is likely that τ^0 and some of $\theta_{(j)}^0$ are no longer statistically different from zero for j = 4, which prevents the parameters from being identified.

Table E2 shows results for Model A3. The models with J = 4 and higher are also unable to estimate. By construction of this model, $\tau_{(j)}^0$ and $\alpha_{(j)}^0$ cannot be identified if $\tau_{(j)}^0$ is zero. It is suspected that $\tau_{(4)}^0$ is close enough to zero.

Next, the following two models are examined as extensions of Model B1;

Model B2

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^{1} \theta_{(j)}^{1} \left(\tau^{1} q_{i(j)} + \alpha^{1} d_{i(j)}\right) + D_{i(j)}^{0} \theta_{(j)}^{0} \left(\tau^{0} q_{i(j)} + \alpha^{0} d_{i(j)}\right) + D_{i(j)}^{0} \theta_{(j)}^{2} \omega^{0} + c_{(j)}$$

Model B3

$$G(.) = \sum_{j=1}^{J} D_{i(j)}^{1} \left(\tau_{(j)}^{1} q_{i(j)} + \alpha_{(j)}^{1} d_{i(j)}\right) + D_{i(j)}^{0} \left(\tau_{(j)}^{0} q_{i(j)} + \alpha_{(j)}^{0} d_{i(j)}\right) + D_{i(j)}^{0} \omega_{(j)}^{1} + c_{(j)}$$

As with previous cases, in Model B2, $f(.)$ is the same as the one in Model B1, while the weights in $g(.)$ are free from a functional restriction. In Model B3, all parameters can vary by proximity orders. Table E3 shows the results for Model B2. In contrary to Model A2, it yields results for all J from 1 to 9 because of the independency among the parameters in this model. τ^0 and α^0 are close to zero as with the results for Model B1.

In [13-5], $\theta^1_{(2)}$ = 0.22 means that the effect of the second closest station with a new line is 22% as significant as the effect of the closest station. It turns out only $\theta^1_{i(2)}$ is the only weighting parameters that has a significant sign. $\omega^0_{(2)}$ = −0.41 implies that the rent is higher by 4,100 yen ($41) for a housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$ and $D^1_{i(2)} = 1$ compared with the rent of a housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$ and $D^1_{i(2)} = 1$. If we assess the rental difference by using the mean distance to the second closest station (0.93 mile) and $q_{i(2)} = 1$, the figure will be about 1,300 yen ($13).

The AICc declines as J increases and hits the minimum at J = 5, implying that the estimation improves by adding the first five closest stations to the model, while adding more than five stations does not contribute to a better result. On the other hand, the BIC hits the minimum at J = 3 and increases as we add more stations in the model, suggesting that only the three closest stations should be considered in the model. This is because the BIC penalizes the number of parameters more than the AICc does.

Lastly, we look at the result for Model B3. Table E4 shows variance inflation factors (VIFs) of hedonic models using all independent variables including those in Model B3 for each J from 1 to 5. Based on the commonly used rule of thumb, where the multicolinearity is considered high regarding a variable with the VIF of 10 or greater, it is observed that the multicollinearity becomes severe once the third closest stations are added to the model. In particular, distances are highly correlated one another.

Table E5 shows the corresponding estimation results, using J = 1 to 5. The shadows of cells indicate degrees of VIFs of variables of the corresponding parameters. Although the unbiasedness still holds as long as the model is correctly specified, magnitudes of parameters for variables with high VIFs should be carefully interpreted. The marginal effect of the number of lines, $\tau^1_{(j)}$, declines as the proximity order becomes lower and the number of lines at the third closest stations has no effect on the rent. However, the fourth and the fifth closest stations show the same magnitude of effects as the second closest station does. The marginal effect of the distance, $\alpha^1_{(j)}$, is only significant for the closest station. Further examinations with more sophisticated measures and extended data are needed to investigate for deeper insights in future research.

Now, the spatial effect of a station without a new line is examined. First, $\tau^0_{(j)}$ are not different from zero for all models. This implies that the number of lines at a station without a new line does not matter to people because they have already access to these lines at closer stations. And $\alpha^0_{(j)}$ shows some positive and significant sings for J = 2 and 3, while the signs are no longer significant after including three or more distances. Lastly, the sign of $\omega^1_{(j)}$ is statistically significant only for j = 2. It is noted, that $\omega^1_{(j)}$ needs to be interpreted with other parameters by taking into account the distance to the jth closest station, as with previous model. The rental difference of housing located in the average distance from the second closest stations (0.93 mile) with and without a new line, having single lines, is about 1,800 yen ($23). When evaluated in the distance of 0.50 miles (the 10th percentile of the distance to the second closest station), the rental difference is about 2,400 yen.

Figure E1 compares the AICc and the BIC of the original proposing models as well as the two generalized models. Model B3 is the most preferable specification according to AICc, while the BIC chooses Model B1 over the other two models. Although the model selection remains an open question for the future research, we suggest in general that researchers compare several models with different levels of functional flexibility. The advantage of a flexible model such as Model A3 and Model B3 is in its ability to discern a general idea of how the $g(.)$ would look like. However, such models come with a cost of a high multicollinearity among variables, which hinders us from having a valid interpretation about parameters of the proximity measures, as well as a high penalty in the information criteria. Once having some understanding of a general relationship between the proximity orders and the weights, one can construct a specific function for $g(.)$ to have a simplified proximity measure. The significant advantage of such a simplified measure is that it allows us to give a clear interpretation of the spatial effect for every site without having increasing penalties on information criteria.

Table E1. Model A2

	[11-1]	[11-2]	[11-3]
$J =$	1	2	3
τ^1	0.39***	0.39***	0.4***
	(0.05)	(0.05)	(0.05)
α^1	−1.52***	−1.59***	−1.47***
	(0.19)	(0.17)	(0.19)
τ^0		0.03	0.00
		(0.02)	(0.00)
α^0		0.83***	3.44***
		(0.20)	(1.08)
$\theta^1_{(2)}$		0.23**	0.15***
		(0.10)	(0.06)
$\theta^1_{(3)}$			0.10**
			(0.05)
$\theta^0_{(3)}$			0.92***
			(0.10)
Log likelihood	−23,630	−23,612	−23,604
AICc	47,352	47,323	47,309
BIC	47,700	47,694	47,695
Observations	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in Model A2. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, ***X***, are not shown in the table.

Table E2. Model A3

	[12-1]	[12-2]	[12-3]
J =	1	2	3
$\tau^1_{(1)}$	0.39***	0.42***	0.44***
	(0.05)	(0.04)	(0.04)
$\tau^1_{(2)}$		0.08	0.08
		(0.06)	(0.05)
$\tau^1_{(3)}$			0.01
			(0.02)
$\alpha^1_{(1)}$	-1.52***	-1.53***	-1.47***
	(0.19)	(0.16)	(0.17)
$\alpha^1_{(2)}$		-1.48**	-1.27*
		(0.70)	(0.66)
$\alpha^1_{(3)}$			0.21
			(0.29)
$\tau^0_{(2)}$		-0.79**	-0.70**
		(0.4)	(0.34)
$\tau^0_{(3)}$			-0.03
			(0.06)
$\alpha^0_{(2)}$		-3.36***	-2.82***
		(0.65)	(0.52)
$\alpha^0_{(3)}$			0.79
			(0.95)
Log likelihood	–23,630	–23,606	–23,586
AICc	47,352	47,311	47,281
BIC	47,700	47,690	47,690
Observations	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model A3. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, $\boldsymbol{X}$, are not shown in the table.

Table E3. Model B2

	[13-1]	[13-2]	[13-3]	[13-4]	[13-5]		
J =	1	2	3	5	9		
τ^1	0.16***	0.16***	0.17***	0.19***	0.18***		
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)		
α^1	−0.48***	−0.52***	−0.58***	−0.59***	−0.59***		
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)		
τ^0		0.06	0.01	-0.01	0.03		
		(0.05)	(0.05)	(0.05)	(0.11)		
α^0		0.30**	0.23*	0.23	0.20		
		(0.14)	(0.13)	(0.15)	(0.16)		
$\theta^1_{(2)}$		0.15*	0.19**	0.22***	0.22***	$\theta^1_{(6)}$	0.03
		(0.09)	(0.08)	(0.08)	(0.08)		(0.11)
$\theta^1_{(3)}$			−0.16	−0.10	−0.10	$\theta^1_{(7)}$	−0.02
			(0.10)	(0.10)	(0.11)		(0.08)
$\theta^1_{(4)}$				0.08	0.07	$\theta^1_{(8)}$	−0.11
				(0.08)	(0.13)		(0.12)
$\theta^1_{(5)}$				0.07	0.11	$\theta^1_{(9)}$	−0.01
				(0.13)	(0.15)		(0.1)
$\theta^0_{(3)}$			0.58	0.57	0.52	$\theta^0_{(6)}$	−0.12
			(0.53)	(0.49)	(0.46)		(0.42)
$\theta^0_{(4)}$				0.19	0.16	$\theta^0_{(7)}$	0.06
				(0.34)	(0.49)		(0.38)
$\theta^0_{(5)}$				0.43	0.17	$\theta^0_{(8)}$	0.24
				(0.56)	(0.72)		(0.41)
						$\theta^0_{(9)}$	0.33
							(0.72)
$\omega^0_{(2)}$		−0.45***	−0.4***	−0.38***	−0.41***	$\omega^0_{(6)}$	0.02
		(0.11)	(0.12)	(0.13)	(0.13)		(0.15)
$\omega^0_{(3)}$			−0.22***	−0.24***	−0.24**	$\omega^0_{(7)}$	−0.01
			(0.08)	(0.09)	(0.09)		(0.14)
$\omega^0_{(4)}$				-0.12	-0.12	$\omega^0_{(8)}$	−0.09
				(0.10)	(0.12)		(0.16)
$\omega^0_{(5)}$				−0.24**	-0.19	$\omega^0_{(9)}$	−0.12
				(0.09)	(0.19)		(0.23)
Log likelihood	−23,607	−23,565	−23,546	−23,533	−23,523		
AICc	47,307	47,230	47,198	47,185	47,190		
BIC	47,655	47,609	47,599	47,631	47,727		
Observations	14,404	14,404	14,404	14,404	14,404		

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model B2. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and coefficients of the control variables, $\boldsymbol{X}$, are not shown in the table.

Table E4. Variance inflation factors (VIFs) in Model B3

[14-1]		[14-2]		[14-3]		[14-4]		[14-5]	
Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
$D^1_{(1)}\times d_{(1)}$	3.44	$D^1_{(2)}\times q_{(2)}$	3.08	$D^1_{(2)}\times q_{(2)}$	3.12	$D^1_{(2)}\times q_{(2)}$	3.17	$D^1_{(2)}\times q_{(2)}$	3.19
$D^1_{(1)}\times q_{(1)}$	4.13	$D^1_{(1)}\times q_{(1)}$	4.30	$D^1_{(3)}\times q_{(3)}$	3.26	$D^1_{(4)}\times q_{(4)}$	3.28	$D^1_{(3)}\times q_{(3)}$	3.29
		$D^1_{(1)}\times d_{(1)}$	7.11	$D^1_{(1)}\times q_{(1)}$	4.68	$D^1_{(3)}\times q_{(3)}$	3.28	$D^1_{(4)}\times q_{(4)}$	3.32
		$D^0_{(2)}\times q_{(2)}$	8.24	$D^1_{(1)}\times d_{(1)}$	7.21	$D^1_{(1)}\times q_{(1)}$	4.79	$D^1_{(5)}\times q_{(5)}$	3.49
		$D^0_{(2)}\times d_{(2)}$	9.40	$D^0_{(3)}\times q_{(3)}$	8.26	$D^1_{(1)}\times d_{(1)}$	7.32	$D^1_{(1)}\times q_{(1)}$	4.82
		$D^1_{(2)}\times d_{(2)}$	9.99	$D^0_{(2)}\times q_{(2)}$	8.84	$D^0_{(3)}\times q_{(3)}$	8.68	$D^1_{(1)}\times d_{(1)}$	7.38
		$D^0_{(2)}$	16.07	$D^1_{(2)}\times d_{(2)}$	16.42	$D^0_{(4)}\times q_{(4)}$	9.07	$D^0_{(5)}\times q_{(5)}$	7.79
				$D^0_{(2)}\times d_{(2)}$	17.58	$D^0_{(2)}\times q_{(2)}$	9.34	$D^0_{(3)}\times q_{(3)}$	8.97
				$D^0_{(2)}$	17.76	$D^1_{(2)}\times d_{(2)}$	16.46	$D^0_{(4)}\times q_{(4)}$	9.23
				$D^1_{(3)}\times d_{(3)}$	18.48	$D^0_{(2)}\times d_{(2)}$	18.06	$D^0_{(2)}\times q_{(2)}$	9.72
				$D^0_{(3)}$	18.55	$D^0_{(2)}$	19.02	$D^1_{(2)}\times d_{(2)}$	16.68
				$D^0_{(3)}\times d_{(3)}$	21.33	$D^0_{(3)}$	19.34	$D^0_{(2)}\times d_{(2)}$	18.15
						$D^0_{(4)}$	20.08	$D^0_{(5)}$	19.14
						$D^1_{(4)}\times d_{(4)}$	33.11	$D^0_{(3)}$	19.74
						$D^1_{(3)}\times d_{(3)}$	33.83	$D^0_{(2)}$	19.87
						$D^0_{(4)}\times d_{(4)}$	41.71	$D^0_{(4)}$	20.61
						$D^0_{(3)}\times d_{(3)}$	42.69	$D^1_{(3)}\times d_{(3)}$	34.10
								$D^0_{(3)}\times d_{(3)}$	43.88
								$D^1_{(5)}\times d_{(5)}$	55.32
								$D^1_{(4)}\times d_{(4)}$	67.25
								$D^0_{(4)}\times d_{(4)}$	92.15
								$D^0_{(5)}\times d_{(5)}$	94.97
Mean VIF	5.08	Mean VIF	6.08	Mean VIF	7.82	Mean VIF	10.65	Mean VIF	15.61
		$5 \leq$ VIF <10		$10 \leq$ VIF < 20		$20 \leq$ VIF < 50		$50 \leq$ VIF	

Table E5. Model B3

	[15-1]	[15-2]	[15-3]	[15-4]	[15-5]
$J =$	1	2	3	4	5
$\tau^1_{(1)}$	0.16***	0.16***	0.17***	0.18***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\tau^1_{(2)}$		0.04**	0.04**	0.04**	0.04**
		(0.02)	(0.02)	(0.02)	(0.02)
$\tau^1_{(3)}$			0.00	0.01	0.01
			(0.02)	(0.02)	(0.02)
$\tau^1_{(4)}$				0.05***	0.05***
				(0.02)	(0.02)
$\tau^1_{(5)}$					0.04*
					(0.02)
$\alpha^1_{(1)}$	−0.48***	−0.56***	−0.59***	−0.59***	−0.6***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
$\alpha^1_{(2)}$		−0.01	−0.15	−0.15	−0.15
		(0.07)	(0.09)	(0.09)	(0.09)
$\alpha^1_{(3)}$			0.22**	0.13	0.13
			(0.09)	(0.10)	(0.11)
$\alpha^1_{(4)}$				0.13	0.15
				(0.10)	(0.12)
$\alpha^1_{(5)}$					−0.10
					(0.15)
$\tau^0_{(2)}$		0.06	0.03	0.03	0.03
		(0.05)	(0.05)	(0.05)	(0.05)
$\tau^0_{(3)}$			−0.01	−0.01	−0.01
			(0.05)	(0.05)	(0.05)
$\tau^0_{(4)}$				0.03	0.03
				(0.05)	(0.05)
$\tau^0_{(5)}$					−0.04
					(0.04)

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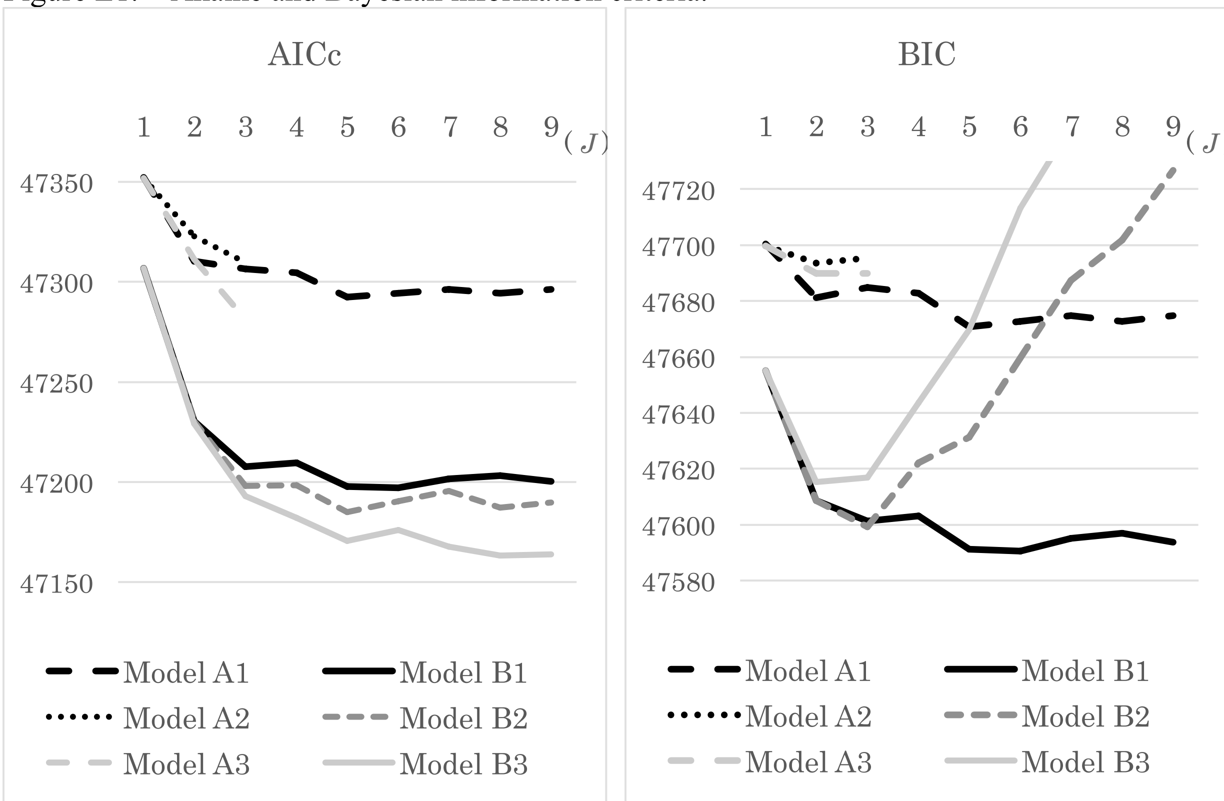
	[15-1]	[15-2]	[15-3]	[15-4]	[15-5]
J =	1	2	3	4	5
$\alpha^0_{(2)}$		0.33**	0.17	0.15	0.17
		(0.14)	(0.17)	(0.17)	(0.18)
$\alpha^0_{(3)}$			0.2**	0.11	0.12
			(0.09)	(0.09)	(0.10)
$\alpha^0_{(4)}$				0.12	0.17
				(0.09)	(0.12)
$\alpha^0_{(5)}$					−0.02
					(0.13)
$\omega^1_{(2)}$		0.39***	0.39***	0.38***	0.38***
		(0.12)	(0.11)	(0.12)	(0.12)
$\omega^1_{(3)}$			0.07	0.06	0.08
			(0.12)	(0.12)	(0.12)
$\omega^1_{(4)}$				−0.04	−0.03
				(0.12)	(0.12)
$\omega^1_{(5)}$					0.04
					(0.14)
R^2	0.8788	0.8795	0.8799	0.8801	0.8803
Log likelihood	−23,607	−23,563	−23,540	−23,530	−23,519
AICc	47,307	47,229	47,193	47,170	47,164
BIC	47,655	47,615	47,617	47,670	47,814
Observations	14,404	14,404	14,404	14,404	14,404

$5 \leq$ VIF <10	$10 \leq$ VIF < 20	$20 \leq$ VIF < 50	$50 \leq$ VIF

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in Model B3. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and coefficients of the control variables, ***X***, are not shown in the table. VIF: Variance Inflation Factor.

Figure E1. Akaike and Bayesian information criteria.



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